Socio-Technical Analysis and Design of Digital Workplaces to Foster Employee Health

Dissertation

zur Erlangung des akademischen Grades
Dr.-Ing.

eingereicht an der
Mathematisch-Naturwissenschaftlich-Technischen Fakultät
der Universität Augsburg

von

Christian Regal, M.Sc. with honors

Augsburg, Dezember 2020

Universität
Augsburg
University

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Datum der Disputation:	26.02.2021

“*It is not the strongest of the species that survives, nor the most intelligent that survives. It is the one that is the most adaptable to change*.“

Charles Darwin

Parts of the research underyling this dissertation was conducted in the PräDiTec project. The author acknowledges the financial support and funding by the German Federal Ministry of Education and Research – BMBF (funding agreement numbers: 02L16D030) for the project PräDiTec – Prävention für gesundes und sicheres Arbeiten mit digitalen Technologien.

Abstract

Recent socio-technical developments caused by ongoing digitalization (e.g., robotic process automation, artificial intelligence, anthropomorphic systems) or the COVID-19 pandemic (e.g., an increasing number of remote working employees and hence, increasing number of virtual collaboration) change the work environment and culture. Digital and smart workplace technologies facilitate business processes and provide tools for efficient communication and (virtual) collaboration, "increasing the productivity of the workforce in the information age" (Attaran et al. 2019, p. 1). Especially in times of the COVID-19 pandemic, digital technologies play a crucial role in keeping us socially close, connected, and collaborative while increasing the physical distance between humans. However, this development affects the health of employees (Tarafdar et al. 2013). In research, for example, it has long been known that the increased usage of digital technologies and media (DTM) may cause stress, leading to potentially harmful reactions in individuals. Research has noted this specific form of stress as technostress (Ayyagari et al. 2011; Tarafdar et al. 2007; Tarafdar et al. 2011; Tarafdar et al. 2019), which is an umbrella term for causes, negative organizational outcomes, and negative humanistic outcomes resulting from the use of DTM at work.

The simultaneous consideration of humanistic (e.g., well-being, equality) and organizational outcomes (e.g., efficiency, productivity) is an integral part of a socio-technical system (Beath et al. 2013; Mumford 2006), which is at the core of the IS discipline (Bostrom et al. 2009; Chiasson and Davidson 2005). However, a review from Sarker et al. (2019) regarding published research articles in one of the top journals within the IS community revealed that most reviewed studies (91%) had focused exclusively on instrumental goals. They conclude that "many IS researchers have forgotten or ignored the premise that technologies need to benefit humankind overall (Majchrzak et al. 2016), not just their economic condition" (Sarker et al. 2019, p. 705). Especially as humanistic outcomes can lead to even more positive instrumental outcomes. Hence, Sarker et al. (2019) call for focusing on the connection between humanistic and instrumental outcomes, enabling a positive synergy resulting from this interplay.

For this reason, this dissertation adopts a socio-technical perspective. It aims to conduct research that links instrumental outcomes with humanistic objectives to ultimately achieve a healthier use of DTMs at the digital workplace. It is important to note that the socio-technical perspective considers both the technical component and the social component privileging neither one of them and sees outcomes resulting from the reciprocal interaction between those two.

Therefore, the dissertation focuses on the interaction while applying pluralistic methodological approaches from qualitative (e.g., semi-structured interviews, focus group discussions) and quantitative research (e.g., collection from a field study or survey research). It provides a theoretical contribution applying both behavioral research (i.e., analysis of cause-and-effect relationships) and design-oriented research (i.e., instructions for designing socio-technical information systems). Overall, this work addresses four different areas within the reciprocal interaction between the social and technical components: the role of the technical component, the role of the social component, DTMs fostering a fit between the technical and social components, and the imminent misfit between these two due to ongoing digitalization.

First, to contribute to an understanding of the technical component's role, this thesis presents new knowledge on the characteristics and features of DTM and their influence on employee health and productivity. Research on the design of digital workplaces examined different design approaches, in which information exchange and sharing documents or project support were regarded (Williams and Schubert 2018). However, the characteristics of DTM also play an essential role in the emergence of technostress (Dardas and Ahmad 2015). This thesis presents ten characteristics of DTM that affect technostress at an individual's workplace, including a measurement scale and analysis on how these characteristics affect technostress. Besides, also, the provision of functional features by DTMs can affect instrumental outcomes or humanistic objectives. For example, affording users with certain kinds of autonomy regarding the configuration of DTM while they work towards their goals could have a tremendous effect on pursuing goals and well-being (Patall et al. 2008; Ryan and Deci 2000). Therefore, this thesis presents knowledge regarding the design of DTM on the benefits of affording users with autonomy. Furthermore, it shows that merely affording more autonomy can have positive effects above and beyond the positive effects of the actualization of affordance.

Second, to contribute to an understanding of the social component's role, this thesis presents new knowledge on contextual and individual factors of social circumstances and their influence on employee health and productivity. In this context, the influence of the COVID-19 pandemic on the intensity of technostress among employees is considered, as work became more digital almost overnight. Therefore, this thesis provides empirical insights into digital work and its context in times of the COVID-19 pandemic and its effect on employees' well-being, health, and productivity. Furthermore, measures to steer the identified effects if the situation in the course of the COVID-19 pandemic persists or comparable disruptive situations should re-occur are discussed. On the other hand, this research takes a closer look at the effect of an individual

preference regarding coping styles in dealing with upcoming technostress. A distinction is made between the effects of two different coping styles, namely active-functional and dysfunctional, on strain as a humanistic outcome and productivity as an instrumental outcome. In the course of this, evidence is provided that coping moderates the relationship between the misfit within the socio-technical system and strain as proposed by the psychological theory of job demands-resources model (Demerouti et al. 2001).

Third, to contribute to a successful fit between the technical and social components, this thesis presents frameworks and guidelines on the design of DTM, which understand the social component (here the user and her/his environment) and adjust accordingly to the needs of their users. Therefore, the thesis provides knowledge on the design of DTMs that support users in applying stress management techniques and build the foundation for stress-sensitive systems (i.e., systems that aim to mitigate stress by applying intervention measures on the social and technical component (Adam et al. 2017)). As a matter of fact, a framework for collecting and storing data (e.g., on the user and her/his environment) is developed and experiences with implementing a prototype for life-integrated stress assessment are reported. The experiences from this and the existing knowledge in the literature will finally be aggregated to a mid-range design theory for mobile stress assessment.

To contribute to the fourth and last aspect, the imminent misfit within the socio-technical system due to ongoing digitalization, this thesis presents new knowledge regarding digital work demands that potentially affect both employees' health and instrumental outcomes. The current version of technostress's theoretical foundation was introduced more than ten years ago by Tarafdar et al. (2007). However, the interaction with and use of DTM has considerably changed along with the societal and individual expectations. Therefore, this thesis puts the current concept of technostress to test. As a result, a new theory of digital stress, as an extension of the concept of technostress, is proposed with twelve dimensions – instead of five dimensions within the concept of Tarafdar et al. (2007) – that could be hierarchically structured in four higher-order factors. This theory holistically addresses the current challenges that employees have to deal with digitalization.

To sum up, this dissertation contributes to the IS community's knowledge base by providing knowledge regarding the interaction between employees and their digital workplace to foster the achievement of humanistic and instrumental outcomes. It provides both behavioral research and design-oriented research while using pluralistic methodological approaches. For this purpose, this thesis presents knowledge about the different components within the socio-technical system, design knowledge on DTMs fostering the fit between these components, and an understanding of an upcoming misfit due to the ongoing digitalization. Overall, this research aims to support the successful change towards a healthy digital workplace in the face of digitalization.

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List of Abbreviations

AVE	*Average Variance Extracted*
CFA	*Confirmatory Factor Analyses*
CFI	*Comparative Fit Index*
CMB	*Common Method Bias*
DO	*Design Objective*
DTM	*Digital Technologies and Media*
EFA	*Exploratory Factor Analyses*
IS	*Information Systems*
IT	*Information Technology*
JDCF	*Java Data Collecting Framework*
JD-R	*Job Demands-Resources Model*
MAP	*Minimum Average Partial*
RMSEA	*Root Mean Square Error of Approximation*
RQ	*Research Question*
SEM	*Structural Equation Modeling*
SRMR	*Square Root Mean Residual*
TLI	*Tucker-Lewis Index*
TMS	*Transactional Model of Stress*

1. Introduction

1.1. Motivation

Recent socio-technical developments caused by ongoing digitalization (e.g., robotic process automation, artificial intelligence, anthropomorphic systems) significantly change the work environment, individual's work, and collective work practices (Barley et al. 2017; Forman et al. 2014). Employees are connected to their digital workplace using cloud services and mobile devices (Mazmanian 2013), physical teamwork is often replaced by work in virtual teams (Gilson et al. 2015), and, while utilizing knowledge-sharing platforms and collaboration tools, communication with others takes place via instant messaging, social media, and teleconferencing. Especially in times of the COVID-19 pandemic, digital technologies and media (DTM) play a crucial role in keeping us socially close, connected, and collaborative while increasing the physical distance between humans. This transformation also influences what is expected to be the "new normal" after the COVID-19 pandemic, when it is anticipated that employees will increasingly work in teleworking settings. However, all of these developments influence employees' health (Tarafdar et al. 2013), affecting their physiological, psychological, and social well-being (World Health Organization 1988).

In the past, political and labor union actors have focused on many different topics (e.g., worker participation in companies, fair pay, annual leave, sick pay, occupational health and safety) (Deutscher Gewerkschaftsbund 2019). The health of employees has also been and remains of central interest here. The physiological aspect of health has been given more attention, which is why various regulations focus on maintaining employee's physiological health. For example, blue-collar workers (i.e., industrial workers and craftsmen) must wear personal protective equipment and participate in safety training, while white-collar workers (i.e., those in office, trade, service, and similar jobs) are encouraged to use ergonomic and stable chairs and low-reflection surfaces. While physiological health is important, the increasing pervasion of DTM at employees' workplaces also strains their psychological health. This risk is currently receiving a great deal of attention from political and labor union actors (CDU, CSU & SPD 2018; Hoffmann 2018).

The changes caused by the rapid development and dissemination of DTM (e.g., virtual and augmented reality, blockchain, internet of things, bring your own device/identity, knowledge graphs, and (explainable) artificial intelligence) are mainly related to the way employees work (often with each other) and how they interact with their workplace (Benson 2002; Miller-Merrell 2012). Employees today are confronted with an unprecedented acceleration of change due to an avalanche of new products and production processes (Cooper 2006) – a development that may lead to worry, uncertainty, and new work environment risks (Cooper 2006). For example, it has long been known that the increased usage of DTM may cause a specific form of stress known as technostress (Ayyagari et al. 2011; Brod 1984; Tarafdar et al. 2007; Tarafdar et al. 2011; Tarafdar et al. 2019). Technostress can, on the one hand, lead to various problematic organizational outcomes (e.g., employees are more dissatisfied with their job, perform worse, and often think about changing jobs or professions) (Gimpel 2019). On the other hand, technostress relates to harmful humanistic outcomes (e.g., employees tend to assess their health status as worse, are more exhausted, and frequently report psychological impairments or illnesses) (Gimpel et al. 2018b). Overall, digitalization is accompanied by problems in balancing work and private life (van Zoonen et al. 2016), increased exhaustion due to availability requirements (Dettmers et al. 2016), quantitative and qualitative work overload (Yun et al. 2012), and a range of other potential challenges to employee health.

A change in German occupational health and safety legislation addressed this issue of increasing psychological demands at work and tried to prevent this. Sect. 5 para. 3 cl. 6 ArbSchG[1] states that employers are responsible for reducing employees' psychological demands at work to a necessary minimum. Accordingly, employers are obliged to conduct regular psychological risk assessments, take appropriate countermeasures if necessary, and document the whole process (sect. 5 para. 1 and 2 and sect. 6 para. 1 ArbSchG). Furthermore, sect. 4 cl. 3 and 5 ArbSchG regulates what should be considered when implementing countermeasures, which aspects should be considered, and how these aspects should be prioritized. Despite this change in the law, there are challenges in practice, both in assessing the psychological risk for employees and in selecting and taking appropriate countermeasures (e.g., choice of the assessment instrument, competence in using an assessment instrument, support in the selection of a measure, and review of the effectiveness of a measure) that make it incredibly difficult for small and medium-sized enterprises to comply with the legal requirements.

Three levers can act as starting points to address the increase in employees' psychological risk the technological lever, the organizational lever, and the individual lever (Schlick et al. 2018).

[1] Occupational Safety and Health Act of 7th August 1996, as amended by the Second Data Protection Adjustment and Implementation Act EU of 20th November 2019

The technological lever refers to the use of well-designed DTMs. The organizational lever refers to organizational structures, processes, and guidelines (e.g., code of conduct, operating instructions, briefing, and workplace design). The individual lever refers to countermeasures that address the individual employee's behavior, whereby this lever is to be used in subordination to the previously mentioned levers. In general, regardless of the lever chosen, state-of-the-art and sound scientific knowledge should be taken into account when selecting and implementing countermeasures. It is precisely this interaction of technological, organizational, and individual aspects and their effect on humanistic and organizational objectives that represent the core of the information systems (IS) discipline (Bostrom et al. 2009; Chiasson and Davidson 2005). Nevertheless, "many IS researchers have forgotten or ignored the premise that technologies need to benefit humankind overall, not just their economic condition" (Sarker et al. 2019, p. 705) and mostly focus on organizational objectives.

1.2. The Role of Digital Technology and Media for Employees' Health

Information technology (IT) is one of the most important driving forces in business in the 21st century (Agarwal and Lucas 2005). Traditionally, the IS discipline examines the interface between IT and organizations (Peffers et al. 2007). In doing this, the IS discipline sees itself as an applied research discipline, frequently adopting theory from other disciplines – most notably economics, computer science, and psychology – to inform a central core of knowledge concerning IT (Agarwal and Lucas 2005). The IS research community values these various points of contact with others (Agarwal and Lucas 2005; Banville and Landry 1989) and calls for further diversity in theoretical foundations and research methods (Robey 1996). In the context of IS research, IT is understood to include technologies involving the development, maintenance, and use of computer systems, software, and networks to process and distribute data to individuals and processes (Merriam-Webster n.d.). However, it should be noted that there are now many different types of IT, most of which are used simultaneously, and they interact with the user as well as with each other. This "combination of information, computing, communication, and connectivity technologies" (Bharadwaj et al. 2013, p. 471) is what will comprise DTM in this dissertation.

The IS research community's identity has evolved since its inception. For example, according to Hevner et al. (2004), IS research investigates the interaction between people, organizations, and technology. Lee et al. (2015) refer to IS as a system consisting of a technology component, an information component, and a social component, where the whole is greater than the sum of its parts. In essence, however, the socio-technical tradition for uniquely studying IT and its relationship with individuals and social collectives (Bostrom and Heinen 1977a, 1977b) is retained, while primary understandings of the individual components and their interaction changes.

Based on this socio-technical tradition, a system itself consists of two self-contained but interacting components. On the one hand, the human-created technical component is “used to solve a problem, achieve a goal or serve a purpose that is human-defined, human perceived or human felt” (Lee et al. 2015, p. 8). It can consist of many different IT components (e.g., hardware and software, digital identities, data, and sources) (Ryan et al. 2002) and, therefore, is used synonymously with DTM throughout this dissertation. On the other hand, social components include humans (as individuals or social collectives) and their relationships and attributes, such as social capital, structures, cultures, and economic systems (Ryan et al. 2002). According to the socio-technical view, neither the technical nor the social component deserves a privileged position: it is the harmonious optimization of both together that matters (Pava 1983; Wallace et al. 2004), as it leads to a balanced and synergistic relationship (Griffith et al. 1998).

Suppose the technical and social components are not properly aligned and there is friction in the reciprocal interaction. In that case, the result will be harmful humanistic outcomes and negative organizational outcomes. In the past, IS mostly focused on instrumental goals, such as efficiency and productivity, since the consideration of humanistic objectives was seen as risky or expensive (Mumford 2000) and, therefore, not economically viable (Sarker et al. 2013a). However, a pure focus on instrumental objectives can, for example, lead to dehumanizing effects (Moore and Piwek 2017), a society focused on efficiency and control (Orlikowski and Scott 2015), technostress (Tarafdar et al. 2007), problematic use of social media (Turel and Qahri-Saremi 2016), and work-life conflict due to technological intrusion (Sarker et al. 2018). These harmful humanistic outcomes can, ultimately, also affect instrumental objectives.

Hence, IS research must not consider both components separately but must, instead, develop knowledge about their reciprocal interaction (Sarker et al. 2019). In addition, Lee, former editor-in-chief of *MIS Quarterly* (one of the most respected journals within the IS research community), argues that neither the social nor the technical should have an “incidental” or minor role in this interaction. The focus on harmony/joint optimization between the technical and the social is important because reciprocal interaction hopefully helps to achieve instrumental objectives (e.g., higher productivity) as well as humanistic objectives (e.g., greater job satisfaction and well-being) (Wallace et al. 2004). It is important to stress that these are not entirely independent of each other. Instead, they influence one another, as the achievement of humanistic objectives can support the realization of instrumental objectives. Figure 1 visualizes the interplay between the technical and social components as well as the humanistic and instrumental objectives resulting from reciprocal interaction.

However, it is necessary to design socio-technical systems properly and, at the same time, understand the effects of the design on the reciprocal interaction between the social and technical components. These different perspectives make a pluralism of methods necessary. For example, methods from the design science paradigm shape the socio-technical system, and the behavioral science paradigm's methods contribute to understanding the resulting change in the reciprocal interaction.

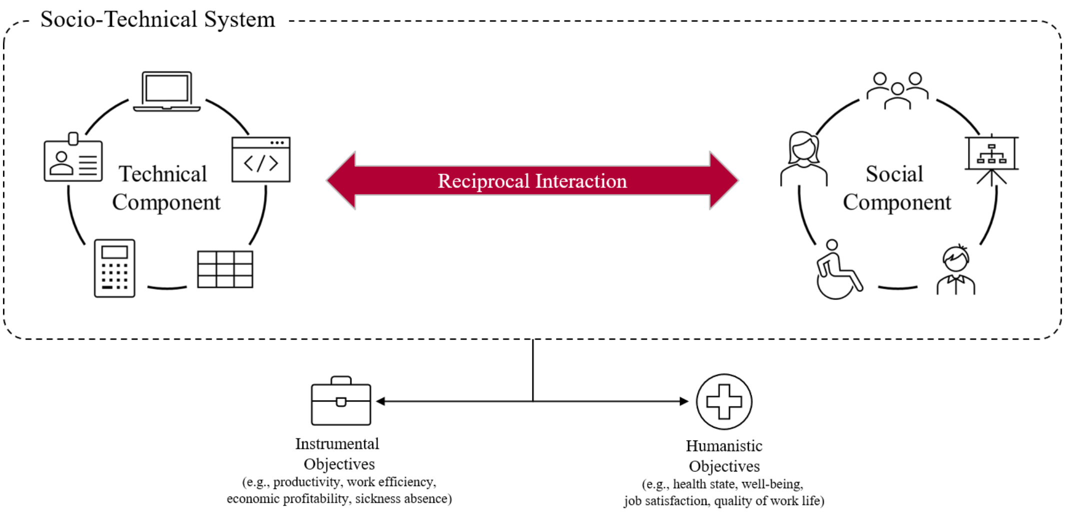


Figure 1: The Socio-Technical System following Sarker et al. (2019)

Although the IS research community has a crucial role to play in achieving humanistic and instrumental objectives, especially in the course of digitization and the transition to the digital workplace, a review by Sarker et al. (2019) shows that published research articles in one of the top journals within the IS community have focused almost exclusively on instrumental goals in the past. Moreover, Goes (2013) concludes that, in reality, very few IS works take a pluralist approach.

1.3.Aim and Outline of this Dissertation

Sarker et al. (2019) call for a focus on the link between humanistic and instrumental outcomes caused by the reciprocal interaction between the technological and social components, which is the core of the IS discipline (Bostrom et al. 2009; Chiasson and Davidson 2005). Responding to this call, the research in this dissertation adopts a socio-technical perspective. It aims to link instrumental objectives with humanistic objectives in order to contribute to the achievement of healthier DTM usage in digital workplaces. It is important to note that the socio-technical perspective considers both the technical component and the social component, privileging neither, and seeks outcomes resulting from the interaction between the two. Therefore, this dissertation focuses on the interaction while applying pluralistic approaches from both qualitative (e.g., semi-structured interviews and focus group discussions) and quantitative (e.g., field study notes and survey research) research methodologies. It provides a theoretical contribution by linking behavioral research (i.e., analysis of cause-and-effect relationships) with design-oriented research (i.e., instructions for designing socio-technical IS). Overall, this work addresses four different areas that are dependent on positionality within the interaction: the role of the technical component, the role of the social component, the role of DTM in fostering a fit between the technical and social components, and the imminent misfit between these two components due to ongoing digitalization.

First, in order to contribute to an understanding of the technical component's role, this dissertation presents new knowledge on the characteristics and features of DTM and their influence on employee health and productivity. Previous research on digital workplaces' design examined different design approaches regarding information exchange and sharing documents or project support without the impact on technostress (Williams and Schubert 2018). In addition, the characteristics of DTM play an essential role in the emergence of technostress (Ayyagari et al. 2011). However, the current literature does not examine individual technologies' characteristics but, instead, asks in general terms about the characteristics perceived by employees in the workplace. The risk here is that employees mix their perception of using many different DTMs, perhaps even with those they use at home. Thus, there is a distortion in the reporting of perception and an inadequate assessment of technology characteristics. Accordingly, it makes more sense to capture the characteristics of the individual DTMs and understand a digital workplace as a combination of several characteristics. This dissertation presents ten characteristics of DTM that affect technostress at an individual's workplace, as well as a measurement scale and analysis of how these characteristics affect technostress. Here, the different characteristic profiles of the DTMs used in the workplace are recorded individually and then combined to form a workplace portfolio profile to avoid biases. Moreover, DTMs functional features can affect instrumental objectives or humanistic objectives. For example, affording users with certain kinds of autonomy regarding the configuration of DTM while they work toward their goals could have a tremendous effect on pursuing goals and well-being (Patall et al. 2008; Ryan and Deci 2000). However, most DTMs that are used to support users in goal attainment mainly focus on an appealing design or a wide selection of features (Zhao et al. 2016) and neglect the potential positive effects of providing autonomy by making a DTM, for example, more adaptable to the user's needs (Pinder et al. 2018). Therefore, this dissertation presents knowledge regarding the benefits of designing DTM to afford users autonomy. Furthermore, it shows that merely affording users more autonomy can have positive effects above and beyond the positive effects of the actualization of the affordances.

Second, to understand the social component's role, this dissertation presents new knowledge on the contextual and individual factors of social circumstances and their influence on employee health and productivity. In this context, the influence of the COVID-19 pandemic on the intensity of technostress among employees is considered. One of the key measures that many companies use to increase their employees' physical distance is telework, enabling employees to remain productive. Therefore, work became digital almost overnight, while DTMs played a crucial role in keeping us socially close, connected, and collaborative. However, this increase in telework and the accountable lockdown as a measure to contain SARS-CoV-2 led to an unparalleled duality of, on the one hand, freeing workers from job design constraints in terms of time, location, routines, and autonomy while, on the other hand, leaving them alone with deficient technical, organizational, and social support. Therefore, this dissertation provides empirical insights into digital work and its context during the COVID-19 pandemic, specifically its effect on employees' well-being, health, and productivity. Furthermore, measures to steer the identified effects if the COVID-19 pandemic persists or comparable disruptive situations should reoccur are discussed. Research has already identified several organizational and individual factors that positively moderate the relationship between stress induced by DTM use and health and organizational outcomes (Srivastava et al. 2015; Tarafdar et al. 2015). All of these beneficial factors are outside the individual's scope of influence. However, little is known about the actual behaviors or thoughts that individuals deploy to mitigate harmful effects. Coping responses concerning technostress are under-studied, and interdisciplinary theoretical enrichment between psychological literature and IS research is needed (Tarafdar et al. 2019). Therefore, this research takes a closer look at the effects of individual preferences regarding coping styles in dealing with increasing technostress. A distinction is made between the effects of two different coping styles, namely active-functional and dysfunctional, on the strain, ultimately threatening humanistic objectives and productivity as an instrumental objective. In the course of making this distinction, evidence is provided that coping moderates the relationship between the misfit within the socio-technical system and strain as proposed by the psychological theory of job demands-resources model (Demerouti et al. 2001).

Third, to contribute to a successful fit between the technical and social components, this dissertation presents frameworks and guidelines for DTM designs that understand the social component (here, the user and her/his environment) and adjust accordingly to their needs users. Several IS researchers have made explicit calls for developing neuro-adaptive IS, which recognize the user's neurophysiological state and positively adapt to it (Riedl 2012; Vom Brocke et al. 2013). For example, Adam et al. (2017) propose a simple design blueprint for stress-sensitive adaptive enterprise systems (i.e., systems that aim to mitigate stress by applying intervention measures to the social and technical components). However, the primary challenge in building such systems is the reliable assessment of employee stress. Therefore, DTM sensing capabilities need to enable a mobile-based, data-driven approach using user, environment, and user-environment interaction data. Various instantiations have already demonstrated such systems' feasibility for different application scenarios (Gimpel et al. 2015, 2019b; Lane et al. 2011; Lu et al. 2012; Wang et al. 2014). However, these systems have many commonalities – for example, regarding their architecture – general guidelines on how to design mobile stress assessment systems do not yet exist. This dissertation provides knowledge on DTM designs that support users in applying stress management techniques, building the foundation for stress-sensitive systems. A framework for collecting and storing data (e.g., on the user and her/his environment) is developed, and experiences with implementing a prototype for life-integrated stress assessment are reported. Based on experiences with this prototype and the available knowledge from previous literature, a design theory for mobile stress assessment is developed.

In order to address the fourth and last aspect, the imminent misfit within the socio-technical system due to ongoing digitalization, this dissertation presents new knowledge regarding digital work demands that potentially affect both humanistic and instrumental objectives. Tarafdar et al. (2007) introduced the current version of technostress's theoretical foundation more than ten years ago. However, the sheer number and functionalities of DTMs have increased enormously since that introduction. Furthermore, interaction with these DTMs has changed considerably due to availability, a changed individual and social view of DTMs, and digitalization expectations. This raises the question of whether the concept of "technostress" is still up to date and suits the prevailing circumstances of the information age in which digital technologies infiltrate all domains of life. Therefore, this dissertation addresses the call for research of Fischer et al. (2019) and puts the current technostress concept to the test. As a result, a new theory of digital stress, as an extension of the concept of technostress, is proposed. This theory includes twelve dimensions – instead of the five dimensions proposed by Tarafdar et al. (2007) – that can be hierarchically structured according to four higher-order factors. This theory holistically addresses the current challenges that employees experience in relation to digitalization.

In sum, this dissertation contributes to the IS community's development by providing knowledge regarding the interaction between employees and their digital workplace in order to foster the achievement of humanistic and instrumental objectives. For this purpose, this dissertation presents knowledge about the components within the socio-technical system, the types of DTM design that foster the fit between these components, and the future misfit due to ongoing digitalization. The theoretical background in Chapter 2 presents foundational knowledge about employee health and the digital workplace, followed by an introduction to methodological approaches in IS research, specifically regarding the interplay between behavioral science research methods and design science research methods. Chapter 3 explores the technical component's role within the reciprocal interaction and provides descriptive and prescriptive knowledge on the characteristics and features of DTM and their influence on employee health and productivity. Chapter 4 explores the social component's role within the reciprocal interaction and provides descriptive knowledge on the contextual and individual factors of social circumstances and their influence on employee health and productivity. Chapter 5 presents DTMs that contribute to a successful fit between the technical and social components and provides descriptive and prescriptive knowledge in the form of frameworks and guidelines for DTM designs that understand the social component (here, the user and her/his environment) and adjust accordingly to the needs of users. Chapter 6 investigates the imminent misfit within the socio-technical system due to ongoing digitalization and provides descriptive knowledge about the feared drawbacks for the social component in future reciprocal interactions with the technical components. Finally, Chapter 7 draws meta-inferences, discusses the results in light of limitations, and provides a future research path. Figure 2 summarizes this dissertation's structure, arranging Chapters 3 through 6 within the reciprocal interaction between the social and technical components.

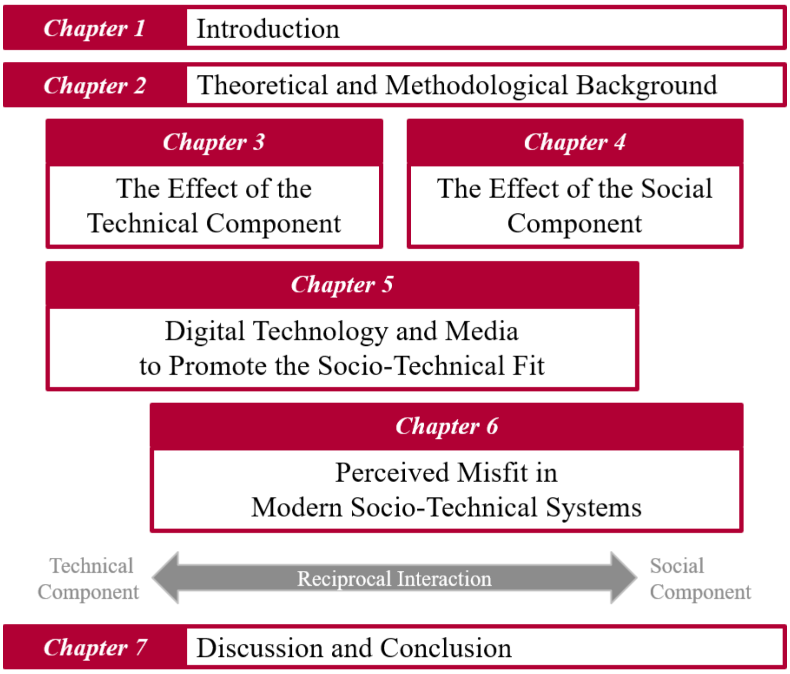


Figure 2: Structure of this Doctoral Dissertation

During the process of developing this dissertation, parts of Chapters 3 through 6 were published in conference papers as part of a regular scholarly discourse or are under consideration for joint publications with coauthors.[2] Major parts of Chapter 3 conform with Becker et al. (2020a) and Gimpel et al. (2020b). Major parts of Chapter 4 conform with Regal et al. (2020) and Becker et al. (2020b). Major parts of Chapter 5 conform with Beckmann et al. (2017), Gimpel et al. (2019b), and Bonenberger et al. (2020). Major parts of Chapter 6 conform with Gimpel et al. (2020a).

[2] This doctoral thesis follows the "Promotionsordnung der Mathematisch-Naturwissenschaftlich-Technischen Fakultät der Universität Augsburg (in der Fassung vom 21.5.2014)" and the "Handreichung des Instituts für Materials Resource Management (MRM) für Doktorandinnen und Doktoranden zur Einbindung von Vorveröffentlichungen in eine monografische Dissertation im Rahmen einer Promotion zum Dr.-Ing. an der Mathematisch-Naturwissenschaftlich-Technischen Fakultät (MNTF) der Universität Augsburg (in der Fassung vom 09.01.2020)".

2. Theoretical and Methodological Background

The following sections are partly comprised of content taken from published research articles included in this dissertation (see Section Aim and Outline of this Dissertation). To improve the readability of the text, I omit the standard labeling of these citations

2.1. Employee Health and Technostress

The World Health Organization (1988) defines health as a "state of complete physical, mental, and social well-being" whereby these three facets influence each other. In the past, the physiological health of employees has always been of primary concern for employers. For example, there are regulations for blue-collar workers (i.e., industrial workers and craftsmen), such as personal protective equipment and safety training, to protect them from negative health consequences. There are also regulations for white-collar workers (i.e., office, trade, service, and similar jobs) that are aimed mainly at the physiological aspect of health, such as frequent rests, ergonomic and stable chairs, and low-reflection surfaces. While physiological health is important, as digitalization inundates the workplace, demands affecting employees' mental health are becoming increasingly relevant (CDU, CSU & SPD 2018; Hoffmann 2018). German occupational health and safety legislation was changed in 2013 to address and prevent this issue of increasing psychological demands at work. Although employers were already responsible for their employees' psychological health, this responsibility became anchored in law via this legislative change; thus, it became more prominent (e.g., employers are obliged to conduct regular psychological risk assessments and take appropriate countermeasures if problems are identified).

The World Health Organization has reported that stress' effect on mental well-being has become one of the health epidemics of the 21st century. The concept of stress has been extensively researched in psychology and biology for many years, resulting in various definitions. While some describe stress from a purely response-based view (Aamodt 2012), others explain stress as an independent variable causing a reaction (Earnshaw and Cooper 2000). This dissertation mainly builds on the Transactional Model of Stress (TMS) from Lazarus and Folkman (1984), one of the most widely-referenced models for understanding human stress in IS research (Adam et al. 2017; Ayyagari et al. 2011; Ragu-Nathan et al. 2008). Lazarus and Folkman (1984) conceptualize stress as a two-way process that involves the production of and response to stressors:

Stress occurs when an individual recognizes that the demands of stimuli are beyond its perceived coping opportunities, which is similar to viewing “perceived stress […] as an outcome variable – measuring the experienced level of stress as a function of objective stressful events, coping processes, personality factors, etc.” (Cohen et al. 1983, p. 386).

The human mind is constantly challenged by physical or psychological stressors (Lu et al. 2012; Riedl and Javor 2012), which can come from internal or external stimuli, that influence our mental or physiological resources (Varvogli and Darviri 2011). Examples of physical stimuli are noise (Smith and Jones 1992), temperature (Jewell 1998), and vibration (Ayyagari et al. 2011). The range of psychological stressors is much broader, but in a workplace context, these might, for example, originate from an organizational context (e.g., work overload (Cooper et al. 2001), corporate culture (Cooper and Cartwright 1994), and role overload (Narayanan et al. 1999). Further, stressors can also result from DTM use (Tarafdar et al. 2007) and different private and individual aspects of human life; for example, positive or negative life events (Holmes and Rahe 1967) can be psychological stressors too.

Stressor consequences are the result of complicated psychological and biological processes. Various sensors in the human body transmit information about the perception of a stressor to the brain. First, the thalamus and frontal cortex receive information from different sensors about the perception of an acute stressor, such as loud music or the breakdown of a computer system (Riedl 2013). Following this, a set of cognitive processes (i.e., mental processes or activities that occur between the processing of the stressor and the associated reaction) start to happen and influence each other (Carpenter 2016). During the cognitive process known as the primary appraisal, the brain unconsciously analyzes the stressor’s importance in terms of taxing or exceeding an individual’s own resources (e.g., objects, conditions, personality traits, energies that are important or useful (Hobfoll and Wells 1998) and classifies stressors as stressful (i.e., taxing or exceeding resources), challenging (i.e., not taxing or exceeding resources), or irrelevant (i.e., no significance for well-being or goal achievement). In addition to assessing a stressor’s relevance, the chances of successful coping (i.e., cognitive and behavioral efforts to master, reduce, or tolerate the stressor (Lazarus and Folkman 1984) are also evaluated. This is particularly relevant if a stressor is classified as “taxing or exceeding resources” in the primary appraisal. In order to address a stressor, another cognitive process – the secondary appraisal – examines the availability of coping resources (such as an individual’s health, energy, social network, support systems, skills for problem-solving, money, tools, and equipment), which form the basis for assessing the chances of successful coping and are relevant for the actual implementation of coping measures later on. It is important to emphasize that the naming conventions of primary and secondary appraisal do not imply a sequential order. On the contrary, they influence each other and work recursively (Carpenter 2016). The interaction of these two has the potential to lead to an immediate short-term stress reaction when resources are taxed or exceeded and the chances of successful coping are low. The stress reaction can be distinguished by physiological, psychological (specifically, cognitive-emotional), and behavioral reactions (Vollmann and Weber 2011). Increased blood pressure, heartbeat, or skin conductivity are indicators of a physiological response. Psychological reactions manifest, for example, in the form of feelings of inner restlessness or dissatisfaction, emotions such as fear or anger, or even in thinking blocks. Behavioral responses include, among others, hasty and hurried behavior (e.g., eating quickly, not taking breaks), non-targeted work behavior, increased conflict behavior toward others, as well as in the form of small nervous tics (e.g., frequently looking at the cell phone, wiggling the foot). It is important to remember that it is possible for a short-term stress response to express itself in many forms.

Depending on the cognitive processes, the limbic system initializes an emotional reaction. The hypothalamus activates the autonomic nervous system’s sympathetic division and releases adrenaline into the bloodstream; this serves as preparation for the “fight-or-flight”-response (Riedl 2013). The parasympathetic division of the autonomic nervous system is also triggered, activating the corticotropin-releasing hormone (Riedl 2013) and triggering adrenocorticotropic hormone release (Riedl 2012), which stimulates cortisol release into the bloodstream (Riedl 2013). Cortisol mediates the physiological and behavioral stress responses (Dickerson and Kemeny 2004; Foley and Kirschbaum 2010) to cope with the immediate stress reaction and achieve a resting state called homeostasis by enhancing blood sugar and delaying unimportant bodily processes, like digestion. While cortisol can lead to positive changes in perception, cognition, behavior, and health, enduring or repeated enhancements of stress hormones may have detrimental long-term effects (e.g., burnout, increased sickness absence, dissatisfaction, etc.).

This immediate (short-term) reaction can be mediated by applying coping measures by employing various response strategies to combat realized or upcoming strain. Gentry (1984) distinguishes between two different types of coping: problem-focused and emotion-focused. In problem-focused coping, the strained person attempts to change or influence the stressful situation. Potential strategies include requesting assistance and social support (Thoits 1995) or removing the stressor by turning down loud music. In contrast, emotion-focused coping attempts to influence the emotional arousal caused by stressors by building mental boundaries (Köffer

2015; Köffer et al. 2015). According to Lazarus and Folkman (1987), the application of coping measures mediates the short-term reaction and, especially, the emotional response.

In addition to this short-term stress reaction in the sense of acute stress, there are also longer-term effects due to the repeated experience of stress reactions. Long-term reactions to stress are commonly referred to as strains; Cassidy et al. (2003) distinguished three types of strains: physical, emotional, and behavioral. Possible physical reactions include the release of the stress hormone cortisol (Riedl 2013), increased heart rate (Trimmel et al. 2003), and elevated blood pressure (Boucsein 2009). Emotional and behavioral strains affect the human psyche, leading to poor judgment (Smith et al. 2014) or moodiness (The American Institute of Stress 2014). It should be noted that the immediate stress reaction, as a short-term reaction, and strains, as a long-term reaction, run parallel. Coping also plays an essential role in long-term reactions (Lazarus and Folkman 1987). However, the role of coping as a mediator or moderator has not yet been clarified in research as it differs according to context, coping measure, and outcome. Thus, some research studies examine coping as a mediator (Bolger 1990; Lazarus 1993; Somerfield and McCrae 2000), some as a moderator (Lin et al. 2010b; Parkes 1994; Pirkkalainen et al. 2019), and some examine both using an exploratory approach (Dardas and Ahmad 2015; Devereux et al. 2009; Frese 1986).

Figure 3 presents the TMS, whereby the temporal order of the process steps is interchangeable, referring to the "recursive" nature of stress (Lazarus and Folkman 1987). Hence, an outcome of a situation (i.e., the situation after the use of coping measures to address a stressor) can become the antecedent of a new situation (in terms of stressors or changes in the availability of personal or coping resources) and vice versa.

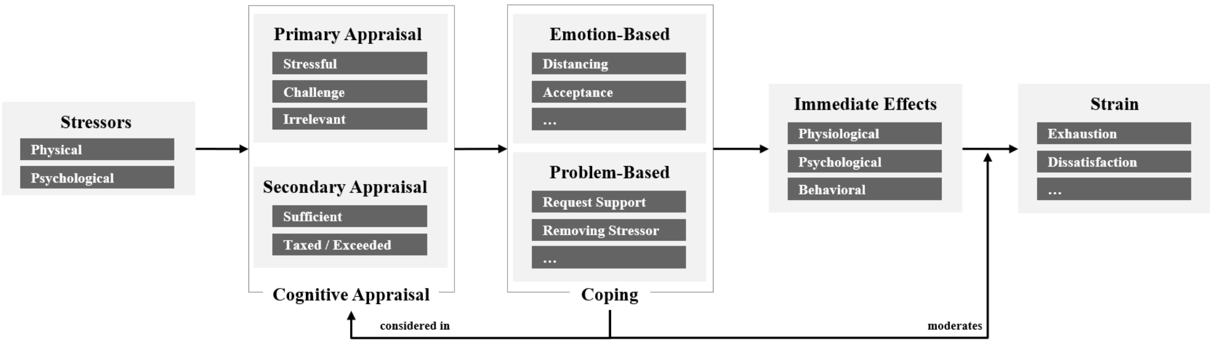


Figure 3: The Transactional Model of Stress[3]

[3] Please note that although not shown here, the TMS is recursive. Furthermore, immediate stress reactions (in terms of short-term effects) and strains (in terms of long-term effects) can occur in parallel.

Previous studies have shown that the usage of DTM may cause stress, leading to potentially harmful reactions in individuals. This specific form of stress has been given the name "technostress" (Ayyagari et al. 2011; Brod 1982, 1984; Tarafdar et al. 2007; Tarafdar et al. 2011; Tarafdar et al. 2019), which is an umbrella term for causes, negative instrumental outcomes, and harmful humanistic outcomes resulting from the use of DTM at work.

Brod (1984, p. 16) introduced the term "technostress" and described it as "a modern disease of adaptation caused by an inability to cope with the new computer technologies in a healthy manner," illuminating the phenomenon from an early perspective. Later, Tarafdar et al. (2007, p. 304) emphasized that "in the organizational context, technostress is caused by individuals' attempts and struggles to deal with constantly evolving [information and communication technologies] and the changing physical, social, and cognitive requirements related to their use." Hence, employees might experience technostress due to an increased usage of DTM in the workplace (Ragu-Nathan et al. 2008).

In their recent review of technostress literature, Tarafdar et al. (2019) classified research on technostress into the following categories: creators, consequences, technological and environmental conditions, moderators of the creators, and outcomes. The five most-cited technostressors are those characterized by Tarafdar et al. (2007) as follows: techno-complexity refers to situations where employees do not feel able to handle job-related DTMs due to a perceived lack of skills; techno-insecurity relates to employees' fear of being replaced by new DTMs or other employees, resulting in job loss; techno-invasion is connected to blurred boundaries between work-related and personal periods; techno-overload consists of situations where employees have to work faster, longer, and harder due to DTM usage; and, finally, techno-uncertainty describes employees' confusion about DTM use caused by new developments regarding technologies applied within the organization.

The described factors may lead to strain as a psychological, physical, or behavioral response to technostressors (Atanasoff and Venable 2017). In this context, several studies have already dealt with different facets of strain, such as mental exhaustion (i.e., feeling burned out and drained (Ayyagari et al. 2011; Srivastava et al. 2015) or problems of psychological detachment (Barber et al. 2019; Santuzzi and Barber 2018). Furthermore, technostress is associated with adverse organizational outcomes, such as lower productivity (Tarafdar et al. 2007; Tarafdar et al. 2015), lower job satisfaction, and lower employee loyalty to the employer (Tarafdar et al.

2011). Hence, technostress is at the core of IS because it affects organizational outcomes and humanistic objectives.

To discover methods and aspects for reducing technostress, Ragu-Nathan et al. (2008) investigated three situational factors and organizational mechanisms. First, technical support can help to reduce technostress when new DTMs are introduced and changed rapidly, forcing users to constantly adapt. Second, literacy facilitation describes an organizational approach in which users are encouraged to share their experiences and knowledge about new DTMs. Third, involvement facilitation means that users are consulted about implementing new technologies and actively encouraged to try them out, reducing technostress. These technostress inhibitors operate as moderators between technostress and job satisfaction, organizational commitment, and continued commitment. Further, individual moderating variables, such as technology self-efficacy (Tarafdar et al. 2015), and personality traits, such as openness, agreeableness, neuroticism, and extraversion (Srivastava et al. 2015), have been identified as factors that influence technostress levels. Ayyagari et al. (2011) emphasized the role different DTM characteristics play in terms of technostress; following this, a user's perception of features of a DTM can lead to stress-creating stimuli, which can create responses and outcomes for the user (strains) (Ayyagari et al. 2011; Salo et al. 2019).

The next subchapter provides more detail about how digitalization has made workplaces even more digital and, thus, posed a greater risk of increasing mental demands and emerging technostress.

2.2. Digital Workplace as Socio-Technical Systems

The term digital workplace is not a neologism in the course of digitalization, as Jeffrey Bier had already introduced it in the early 1990s. Since then, our understanding of a digital workplace has undergone several fundamental shifts. Recent socio-technical developments caused by ongoing digitalization (e.g., artificial intelligence, robotic process automation, anthropomorphic systems, etc.) or the COVID-19 pandemic (e.g., an increasing number of remote employees, which has led to an increasing amount of virtual collaboration) have dramatically changed the work environment. The additional rapid development and dissemination of DTM have further changed the way employees work, as well as how they interact with their workplaces (Benson 2002; Miller-Merrell 2012). As a result, the traditional ways of working are gradually being abandoned in favor of DTM use (Gimpel 2019; Mulki et al. 2009).

The change has taken and is taking place on both the technical and organizational levels. Shorter technology cycles accelerate the process of change, and new challenges become more pressing. In most cases, it is not the technical innovations that pose problems for companies but, rather, the organizational ones (Afreen 2014). Nowadays, employees are often connected to their workplace through cloud services and mobile devices, a phenomenon that profoundly affects the balance between work life and private life (Mazmanian 2013). Additionally, regular physical teamwork is more often replaced by work in virtual teams (Gilson et al. 2015), meaning that communication with others takes place via instant messaging, social media, and teleconferencing, while collaboration occurs through the utilization of knowledge-sharing platforms and collaboration tools (Colbert et al. 2016; Haas et al. 2015).

Therefore, the objective in designing productive digital workplaces, which has gained relevance in past years, is to improve collaboration and communication within the organization (Yalina 2019). DTMs facilitate business processes and provide tools for efficient communication and (virtual) collaboration, "increasing the productivity of the workforce in the information age" (Attaran et al. 2019, p. 1). Digital workplace design is crucial for employees' productivity, especially for knowledge workers (Köffer 2015; Yalina 2019). However, what a digital workplace is and how it is defined is rather general and aspirational when described in the literature. In an effort to grasp the essence of digital workplaces, Williams and Schubert (2018) reviewed academic and practical literature and identified three thematic categories: organization, people and work, and technology.

First, organization refers to a change in corporate culture in the process of creating a new workplace design. This is intended to lay the foundation for a suitable framework for the design of digital workplaces. For example, from a material point of view, the digital workplace requires, in a narrower sense, a change in space design and available equipment, as well as, in a broader sense, location-based and temporal flexibility. Williams and Schubert (2018) go even further and state that location is irrelevant for a digital workplace, regardless of whether tasks are performed alone or with others. Especially during the COVID-19 pandemic, DTMs, which provide flexibility regarding where and when employees work, play a crucial role in keeping us socially close, connected, and collaborative while increasing the physical distance between humans. Sophisticated mobile devices allow white-collar work to take place anytime, anywhere (Davis 2002). Some companies have even considered partially or entirely (e.g., the Git-repository hosting service provider GitLab and the web search engine DuckDuckGo) eliminating traditional offices (Mulki et al. 2009). Especially for white-collar workers, the barriers in time and space are no longer determined by technological constraints. From a cultural point of view, the introduction of digital workplaces is accompanied by a fundamental change in organizational structures and the culture of communication and collaboration. Therefore, Dery et al. (2017) argued that responsive leadership is essential. This kind of leadership refers to how management prioritizes the activities that focus on the development and continuous improvement of the employee experience in the organization. A change in management mindset is necessary to support this shift in focus. Examples of responsive leadership include facilitating workplace design, being open to employee opinions, providing time and space for feedback, remaining curious about new technologies and new approaches to work, and focusing on systemic learning.

Second, employee acceptance is also of central importance to a successful transition to a digital workplace. Therefore, a key strand in all definitions is a focus on people and work. The digital workplace should provide the conditions that enable people to be productive in their work (Drakos 2019; Marshall 2015; Robertson 2015). It should also be predictive and intelligent "so that it is able to anticipate the requirements of the user for data, information and knowledge" (White 2012). Specific emphasis is given to supporting information/knowledge work, employee engagement, collaboration, and information sharing (White 2012). Specifically, Dery et al. (2017) emphasized that employee connectedness is crucial for effective digital workplaces. For this reason, employees' literacy skills need to be developed (Bahadur and Yadav 2015) so that they can use today's available technology effectively (van de Velde and Hantson 2011). The employees who are most harmed by digital workplace shifts are those who lack the necessary support to help them develop the skills and capabilities needed to make successful use of technology (Eisenberg et al. 2006; Goad 2002). Pemberton and Robson (1995) suggested frequently evaluating employees' skills and offering advanced training to ensure practical skill development.

Third, definitions of the digital workplace focus heavily on underlying technologies, characterizing them as an integrated platform that provides all of the tools and functionality required to support people and their work practices while enabling flexible and integrated working conditions (Robertson 2015; White 2012). Hence, a digital workplace contains a collection of DTMs that enable new and more effective ways of working while raising employee engagement and agility, as well as taking advantage of consumer-oriented styles and technologies (Gartner 2020). Bharadwaj et al. (2013, p. 471) defined digital technologies as "combinations of information, computing, communication, and connectivity technologies" and referred to the importance of the interplay of digital technologies, which include social, mobile, analytics, cloud technologies, and the Internet of Things (Sebastian et al. 2017). A productive digital workplace is characterized by the ability of every stakeholder to access digital technologies and the possibility of interaction without any physical limitations (Dahlan et al. 2018). Digital technologies can be characterized in different ways depending on the point of view (e.g., along with their physical components, depending on the data treatment, or whether humans are involved or not) (Berger et al. 2018). Overall, prior research has taken different perspectives to analyze the impact on technostress. For example, to focus on abstract characteristics of single digital technologies (Hung et al. 2015; Salo et al. 2019; Westermann et al. 2015) or the focus on digital technologies in general (Ayyagari et al. 2011; Tarafdar et al. 2007).

These three categories are continually changing in the course of digitalization, and these changes have an impact on employees and their health via the digital workplace. To understand the relationship between the different aspects of a workplace and humanistic and instrumental outcomes, Bakker and Demerouti (2007) developed their Job Demands-Resources Model (JD-R). According to the JD-R model, different workplace aspects can be categorized as either job demands or job resources. Job demands are physical, psychological, social, or organizational aspects of the job that require an individual's effort and skills. These demands also form the foundation of internal or external stimuli, which are described as stressors by the TMS.[4] Examples of such job demands are workload, organizational changes, emotionally demanding interactions, and computer problems. In contrast, job resources are aspects of the workplace that help achieve goals, reduce job demands, or foster personal growth, learning, and development (Bakker and Demerouti 2007; Demerouti et al. 2001). Put in the language of the TMS, these job resources can either strengthen employees' mental resources (i.e., their personal resources) or form the foundation for the application of coping measures.[5] Examples of personal resources include resilience, self-efficacy, optimism, and some facets of personality. Autonomy, feedback, coaching, team climate, and support are examples of job resources. Where the TMS categorizes all long-term effects as strain, the JD-R tries to determine the effects of the complex interplay of demands and resources in terms of the motivation and health of employees. For example, deficiencies in work design or persistent excessive stress factors lead to the exhaustion of employees' mental and physical resources, which can have deleterious health effects. Simultaneously, resources reduce the influence of job demands on health-related effects (Bakker

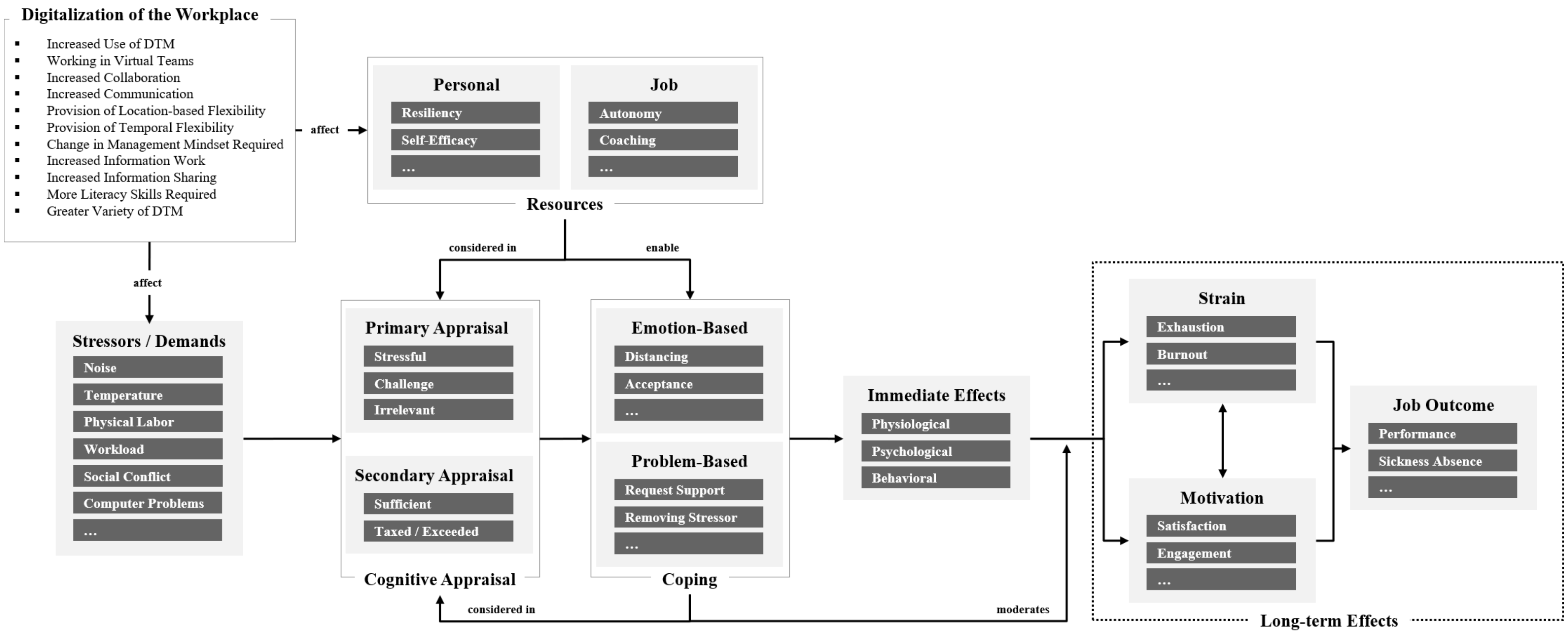
[4] In the remainder of this dissertation, the terms "stressor" and "demand" are used synonymously and refer to internal or external stimuli that have the potential to induce stress.

[5] In the remainder of this dissertation, the term "resource" refers to both an employee's personal resources and the job resources that either strengthen personal resources or provide opportunities for coping.

and Demerouti 2007; Xanthopoulou et al. 2007). Additionally, the availability of resources can lead to high commitment, low cynicism, and intrinsic motivation. Consequently, resources and coping measures play an important role in dealing with demands and influence the relationship between these and the resulting effects. Ultimately, the motivation and health of the employee determine the organizational outcomes.

Regarding digital workplaces, the complex interplay of physical, cultural, and technological arrangements leads to new demands (e.g., blurring boundaries between private and business life and constant changes regarding the availability and functionality of DTMs). At the same time, new job resources (e.g., location-based and temporal flexibility and DTMs' ability to adapt to users' needs) for dealing with these arise and become necessary. This results in changes in health-related and work-related effects, as well as influencing job performance. Hence, the JD-R reflects the close connection between humanistic and instrumental outcomes and is, therefore, suitable for research from a socio-technical perspective, while the TMS provides a sound foundation for understanding cause-and-effect relationships regarding stress.

Figure 4 visualizes the causal relationships and interrelations. The model illustrates the relationships between the individual terms, embeds them in a common context, and focuses on the concepts upon which this dissertation is based. The model does not claim to be complete and is simplified in some parts for purposes of comprehensibility.



Note: Although not shown here, the model is recursive. Furthermore, immediate stress reaction (in terms of short-term effects), and strains and motivation (in terms of long-term effects) can result in parallel.

Figure 4: Relationships and Interrelations within the TMS and the JD-R Model.

2.3.Research Methods in Information Systems

Two research paradigms are predominant in the IS research community: behavioral science and design science (March and Smith 1995). While the original differentiation was between "design science" and "natural science," Hevner et al. (2004) favored the label of "behavioral science" over "natural science," as the IS discipline is considered to be more of a social and business science than a natural science.

The behavioral science paradigm seeks to develop and justify theories that explain and predict organizational and human phenomena while analyzing, designing, implementing, and applying IS (Hevner et al. 2004). Hence, behavioral science is theory-based and empirical. It describes what is and tries to explain why it is so, thus extending propositional knowledge or the so-called Ω-knowledge (comprising descriptive and explanatory knowledge). In contrast, the design science paradigm aims to "add to knowledge of how things can and should be constructed or arranged (i.e., designed) […] to achieve a desired set of goals" (Hevner et al. 2019, p. 3). Hence, design science relies on existing natural or behavioral theories to derive technical components that act in socio-technical systems (Hevner et al. 2004), thus extending applicable (or prescriptive) knowledge or λ-knowledge (Gregor and Hevner 2013).

Hevner et al. (2019) distinguished six different roles research can adopt in relation to behavioral science and design science. Role 0 extends the Ω-knowledge-base by understanding the problem space. Role one to role four extend the λ-knowledge-base by providing prescriptive knowledge about the design of DTM. Role 1 refers to the design of a technical component that is built and evaluated over multiple, iterative rounds (Sonnenberg and Vom Brocke 2012), role two refers to the design of a technical component and the associated processes and procedures for its deployment and use, role three refers to the design of a technical component as well as the (re)-design of an entire socio-technical system, and role four refers to development or refinement of new design theories. The last role, role five, refers to the usage of a DTM as a creativity tool within a design science research project; hence, it does not provide knowledge to the Ω-knowledge-base or the λ-knowledge-base. Within a single design journey, several research activities can take place, each taking on a different role, leading to the continuous refinement and development of knowledge (Vom Brocke et al. 2020). In each research activity, however, a knowledge chunk (i.e., a reproducible research activity that results in evaluated knowledge) is created that enables progress within the design journey (Vom Brocke et al. 2020).

Although behavioral science and design science are two separate research paradigms, Hevner et al. (2004) argued that both should complement one another. They may compete for scarce resources (e.g., research effort, time, money), but they also share the same perspectives. They ask different questions or solve different problems using different methods and approaches, but their questions and methods are not incommensurable (Strangmeier 2008). However, there is a clear difference in temporality between these two research approaches (Hevner et al. 2004). Behavioral science is seen as reactive and retrospective, as it looks backward and tries to explain what already exists. In contrast, design science is legitimated through proactively creating technological solutions for the future. It works to develop new artifacts as responses to identified problems and needs. Hence, March and Smith (1995) characterized behavioral science as providing “descriptive” knowledge and design science as providing “prescriptive” knowledge.

Researchers must draw from both knowledge bases to develop valuable new artifacts or investigate artifacts in use (Gregor and Hevner 2013). Studies in behavioral science focus on understanding the social component’s behavior in interaction with the technical component by applying data collection techniques and ultimately deriving explanations and descriptive knowledge. These explanations and knowledge (i.e., the truth of explained use behavior) inform the development of theories and guidelines for creating artifacts by applying design research methods (e.g., action design research). Design science aims to create and evaluate technical components that offer possible solutions to identified problems (i.e., the utility of newly designed artifacts). The designed components can then be applied within a socio-technical system in order to understand the relationship between the social component and the technical component – and, thus, the effect on reciprocal interaction (as a focal point within behavioral science) – or to provide data collection techniques (as a facilitator for behavioral science). Figure 5 visualizes the interaction between design science research and behavioral science research and shows how they enrich each other.

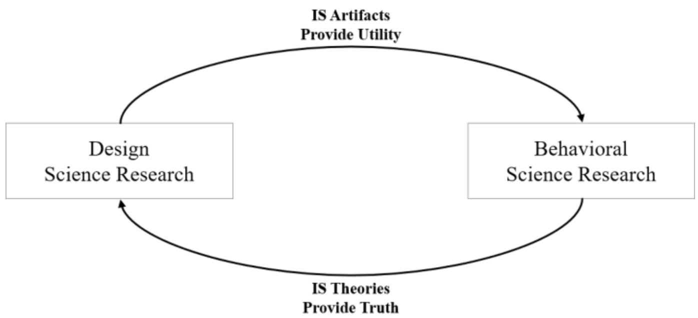


Figure 5: The Relationship between Design Science and Behavioral Science

Both paradigms use different research methods, which can be categorized into three groups. First, qualitative research methods are based on constructive paradigms (i.e., appropriate methods overcome “the naive findings of the world” and enable the construction of knowledge and science) and focus on analyzing narrative data (Tashakkori and Teddlie 2003b). Examples of qualitative research methods are expert interviews, focus group discussions, prototyping, and literature analysis. Second, quantitative research methods are based on positivist paradigms (i.e., knowledge is based strictly on evidence that is genuine, perceptible to the senses, and verifiable) and focus on analyzing numerical data (Orlikowski and Baroudi 1991). Examples of quantitative research methods are laboratory or field experiments, surveys, and simulations.

The combination of qualitative and quantitative research methods comprises the third category. Mixed-methods research techniques are based in multiple paradigms and focus on analyzing both narrative and numerical data (Tashakkori and Teddlie 1998a, 2003a). Generally, mixed-methods research designs should be distinguished from the often synonymously used term, multi-method research designs (Mingers 2001), as they differ conceptually (Venkatesh et al. 2013). A mixed-methods research design utilizes quantitative and qualitative research methods (e.g., survey and focus group interviews, prototyping, and field experiments) to answer the research questions (Tashakkori and Teddlie 2003a). In contrast, a multi-method research design focuses either on applying multiple qualitative (e.g., case study and expert interviews) or multiple quantitative research methods (e.g., laboratory and field experiment) (Teddlie and Tashakkori 2003). Mixed-methods designs offer the ability to “address confirmatory and explanatory research questions,” to “provide stronger inferences than a single method or worldview,” and to “produce a greater assortment of divergent and/or complementary views” (Venkatesh et al. 2016, p. 437). Similarly, Creswell (2014, p. 216) argued that researchers “gain a complete understanding of the research problems” by using mixed-methods strategies. Moreover, mixed-methods approaches are seen as desirable in IS research with respect “to understanding and explaining complex organizational and social phenomena” (Venkatesh et al. 2013, p. 22). Hence, a mixed-methods approach is considered suitable for the analysis and design of socio-technical systems in the context of work.

This doctoral dissertation applies both behavioral and design science paradigms in primarily mixed-methods research designs to enable more complementary insights into the socio-technical system in the context of work in order to derive a more profound understanding of the reciprocal interaction between the social component and the technical component, ultimately producing both descriptive and prescriptive knowledge. The dissertation’s overall objective is to add to the body of knowledge regarding the design of socio-technical systems that link both instrumental and humanistic objectives to ultimately achieve a healthier use of DTMs in digital workplaces.

Chapter 3 engages both behavioral science and design science and employs qualitative and quantitative research methods to gain descriptive and prescriptive knowledge about the technical component related to reciprocal interaction. Chapter 4 mainly engages behavioral science and employs mixed-methods approaches to gain descriptive knowledge about the social component related to reciprocal interaction. Chapter 5 engages both behavioral science and design science and employs qualitative and quantitative research methods to gain descriptive and prescriptive knowledge about the technical component fostering the reciprocal interaction with the social component. Chapter 6 engages behavioral science and employs a mixed-methods approach to gain descriptive knowledge about the social component's perceived misfit in the future reciprocal interaction with the technical component.

3. Analyzing the Effect of the Technical Component

The digital workplace of employees consists of both technical and social components, whereby technical components are designed to "solve a problem [or] achieve a goal" (Lee et al. 2015, p. 8), thereby supporting employees in the context of social components. Nowadays, technical components as DTMs are taking on a variety of forms, such as enabling employees to stay connected to the digital workplace from anywhere via cloud services and mobile devices (Mazmanian 2013), offering different types of communication services with varying degrees of media richness, or enabling knowledge-sharing platforms and collaborative tools (Colbert et al. 2016; Haas et al. 2015). Over the course of this process, Ayyagari et al. (2011) emphasized the role different DTM characteristics play in terms of technostress; based on this, a user's perception of the features of a DTM can lead to stress-creating stimuli, which can create responses and outcomes for the user (strains) (Ayyagari et al. 2011; Salo et al. 2019). Therefore, the research within this chapter focuses on the technical component's characteristics and features, as well as their influence on employee health and productivity. Section 3.1 presents descriptive knowledge regarding characteristics of DTM that affect technostress at an individual's workplace, including a measurement scale and analysis on how these characteristics affect employee health. Subsequently, Section 3.2 presents prescriptive knowledge regarding the design of DTM upon the benefits of affording users autonomy and the effect on employee health and productivity. Major parts of Chapter 3 conform with Becker et al. (2020a) and Gimpel et al. (2020b).

3.1. Analyzing the Effect of Technology Characteristics

Digitalization, driven by a wide variety of DTMs, has led to multifaceted changes for individuals, economies, and society (Fitzgerald et al. 2013; Gimpel et al. 2018a). DTMs are ubiquitous in private but also in business lives. They have changed the workplace from a narrowly defined and time-bound place to a partly virtual and temporally and locally independent existence (Zuppo 2012). At the beginning of the year 2020, the COVID-19 pandemic led to the imposition of confinement or contact restrictions in many countries. Work was transferred to home offices where possible. For many, this meant a new level of virtual work. This may have a long-term impact on the equipment of many workplaces with DTMs and their use even after the end of the pandemic.

DTMs include devices like smartphones or tablets but also applications that can facilitate business processes by providing tools for inter- and intra-organizational communication and collaboration (Zuppo 2012). Today's workplace does not only consist of a single DTM but many, which enable effective ways of working (Gartner 2020). The design of the digital workplace has become an important factor in increasing the productivity of knowledge workers (Köffer 2015). However, the increased usage of DTMs in the changing world of work may cause technostress, leading to potentially negative reactions in individuals (Ayyagari et al. 2011; Tarafdar et al. 2007; Tarafdar et al. 2011; Tarafdar et al. 2019).

In the last years, researchers focused on different aspects of technostress, including technostress creators (e.g., Tarafdar et al. (2007)), strains (e.g., Gimpel et al. (2018b)), technostress inhibitors (e.g., Ragu-Nathan et al. (2008)) and coping behaviors (e.g., Pirkkalainen et al. (2019)). Ayyagari et al. (2011) emphasized the question of which role the different characteristics of DTMs play in terms of technostress. The characteristics of DTMs refer to the functional and non-functional features perceived by the user, which can be pursued directly or indirectly. Many other researchers followed the call of Ayyagari et al. (2011) that their list of proposed characteristics might not be exhaustive and that the introduction of new DTMs in the future might also result in new characteristics. Therefore, Maier et al. (2015) analyzed characteristics of enterprise resource planning systems, Salo et al. (2019) focused on characteristics of social network services, and Hung et al. (2015) regarded mobile phone characteristics influencing technostress. In summary, there exist additional characteristics resulting from further research focusing on specific technologies or contexts that extend the list of Ayyagari et al. (2011). However, to eliminate the black box phenomenon between DTMs and technostress, further research is needed. Currently, there is no research that uses the extended list of characteristics to analyze their influence on technostress and no review of whether there are also other characteristics beyond that.

Furthermore, Ayyagari et al. (2011) analyzed the influence of DTM characteristics on technostress by incorporating all DTMs that are used at the workplace of their respondents without referring to a specific DTM. Therefore, it is not ensured that respondents only think about one DTM they use at work when answering the questionnaire. Instead, it is conceivable that the respondents mix their perception of using many different DTMs, maybe even with those they use at home. This is also one of the significant drawbacks that Ayyagari et al. (2011) mentioned themselves in their limitations section. However, analyzing the relation between the characteristics of one specific DTM and technostress might seem to be by far more precise and concrete, as it does not mix-up and allow for bias when participants have different technologies in mind. On the other side, it does not properly reflect reality. Typically, people use a combination, and hence, the assessment of technostress incorporates the experiences with multiple DTMs and not only with a specific DTM. However, there are no considerations to assess the characteristics of specific DTMs building DTM profiles in order to summarize these across all DTMs used at the user's workplace to explain the connection with technostress. Research on the design of digital workplaces examined people-focused and process-focused design approaches, in which information exchange and sharing documents or project support was regarded, without the impact on technostress (Williams and Schubert 2018). Therefore, an understanding of the characteristics of DTMs, their interplay at the workplace, and how they influence technostress will be valuable as it can assist developers of digital technologies and designers of workplaces in a way that can prevent technostress.

Therefore, we aim to add to technostress literature by addressing the following three research questions (RQ):

RQ1) Which characteristics of digital technologies with relation to technostress exist?

RQ2) How does the characteristic profile of specific digital technologies look like?

RQ3) What is the influence of characteristic profiles of digital technologies used at the workplace on technostress?

In order to answer our research questions, we apply a mixed-methods design. First, we conceptualize the relevant characteristics of DTMs based on extant literature and qualitative research. Next, to be able to evaluate the characteristics quantitatively, we collect existing item scales, develop new multi-item scales where necessary, and perform an initial reliability and validity test of our scales via card-sorting and a quantitative pre-test. Then, we further validate the scales in a large-scale survey with both exploratory factor analyses (EFA) and confirmatory factor analyses (CFA). Based on survey data, we develop characteristic profiles of multiple specific DTMs used at the respondent’s workplace and determine their influence on technostress using structural equation modeling (SEM).

Section 3.1 is structured as follows: The first subsection introduces the theoretical background, including the characteristics of DTMs that have already been found to influence technostress. Following this, the methodology is presented, while the subsequent subsection describes the development of the DTM profiles based on interviews with experts and focus groups as well as a survey with 4,560 users of digital technologies in different organizations. The next subsection analyzes the relationship between the developed DTM profiles of specific technologies with technostress. Finally, the last subsection within Section 3.1 discusses these results and concludes this section.

Theoretical Background

The objective of digital workplaces is to improve collaboration and communication in the organization (Yalina 2019). Digital workplaces are characterized by the set of DTMs provided to execute one's work effectively, irrespective of the location, and whether the task is performed alone or with others (Williams and Schubert 2018). Bharadwaj et al. (2013, p. 471) refer to the importance of the interplay of DTMs. Elements of a digital workplace include DTMs accessible by every stakeholder and interaction is possible without any physical limitations (Dahlan et al. 2018). The design of a digital workplace is crucial for the worker’s productivity, especially for knowledge workers (Köffer 2015; Yalina 2019). Dery et al. (2017) illustrated how one could successfully design digital workplaces to drive organizational success. They mention that positive employee experiences of collaborating with others and dealing with the complexity of digital workplaces enable innovation and name possible improvements for the digital workplace, including fast log-in and mobility, but do not consider the possible effects on the individuals‘ well-being.

Besides the positive effects of the use of DTMs including an increase in productivity, effectiveness, and efficiency (Bharadwaj 2000; Melville et al. 2004), research has shown the potential of DTMs to cause technostress (Brod 1984; Ragu-Nathan et al. 2008). Technostress is not created by a DTM itself but emerges from the interaction of human users with DTMs. Whether technostress emerges depends on the user’s resources, capabilities, assessments, and the type of DTM (Gimpel 2019). Ayyagari et al. (2011) developed a technostress framework consisting of the main concepts of stress (technostress creators and strains) and the IT artifact consisting of DTM characteristics (see Figure 6).

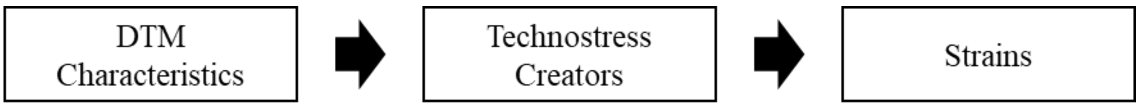


Figure 6: Technostress Framework by Ayyagari et al. (2011)

Following this framework, a user’s perception of features and attributes of a DTM (DTM characteristics) can lead to stress-creating stimuli, which again create responses and outcomes for the user (strains) (Ayyagari et al. 2011; Salo et al. 2019). The most recorded strain is the negative effect on end-user satisfaction, followed by job satisfaction, performance, productivity, and organizational commitment (Sarabadani et al. 2018). Tarafdar et al. (2007) stated that higher technostress results in lower productivity. Ragu-Nathan et al. (2008) showed that technostress creators decrease job satisfaction as well as organizational and continuance commitment. Both are emphasized by Tu et al. (2005), who found that next to lower productivity, also higher employee turnover can result out of technostress. Concerning individuals' health, Mahapatra and Pati (2018a) found that, in an Indian context, techno-invasion and techno-insecurity can lead to burnout, which, in turn, is associated with several negative outcomes on the organizational and individual level including lower productivity, job satisfaction, and higher absenteeism as well as depression and anxiety (Maslach et al. 2001). For German employees, Gimpel et al. (2018b) found that higher levels of technostress go along with a higher number of people reporting to suffer from headaches, fatigue, sleeping problems, and exhaustion, for example.

DTMs can be characterized in different ways depending on the point of view, e.g., along with their physical components, approaches, and concepts (Berger et al. 2018). Concerning the link of DTMs with technostress, prior research analyzed characteristics of single DTMs (Hung et al. 2015; Salo et al. 2019; Westermann et al. 2015) or DTMs in general (Ayyagari et al. 2011; Tarafdar et al. 2007). Analyzing social networking services as one DTM, Salo et al. (2019) found two main characteristics: (1) self-disclose features regarding information about oneself and (2) information cue paucity referring to the limited, one-sided information delivery. Hung et al. (2015) characterized mobile technologies by high accessibility, mobility, ubiquity, and connectivity. Additionally, Westermann et al. (2015) found that push notifications are often assessed to be disturbing, which can also be seen as a characteristic. Ayyagari et al. (2011) defined characteristics of DTMs in general based on how individuals perceive them in use. Ayyagari et al. (2011) found six characteristics categorized in usability, dynamic, and intrusive features. Usability features are usefulness, complexity, and reliability. The single dynamic feature is the pace of change. Intrusive features are presenteeism and anonymity. Adding to these six characteristics, Tarafdar et al. (2019) mention mobility.

Research Process

As we strive to answer three interconnected questions, our research process is divided into three parts, each of them applying a combination of various methods. We conduct a mixed-methods approach, as described by Venkatesh et al. (2013). It includes and integrates qualitative as well as quantitative investigations, which, according to Venkatesh et al.'s (2013) scheme, serve developmental purposes.

First of all, we aim to identify the characteristics of DTMs that relate to technostress. For identifying and conceptualizing the characteristics of DTMs, we follow steps one to six of the process of MacKenzie and Podsakoff (2011). We conduct a literature research and interviews with experts and focus groups. Based on this, we develop multi-item survey scales for the characteristics of specific DTM. The scales and individual items are refined based on results from card-sorting regarding their content and face validity. Next, we perform a pre-test and an exploratory factor analysis (EFA) and, again, refine the scales and individual items.

Second, the resulting scales are then used in a large-scale quantitative survey. For the validation, the data is split into two random subsets. On the first subset, an additional EFA is carried out to examine the revised items. Finally, a CFA is performed on the second subset to validate the scales. Furthermore, we used the data to calculate a normed characteristics profile for specific technologies by aggregating the answers across many respondents.

Third, as we argue that technostress does not solely depend on the usage of a single DTM but on the combination of all DTMs used at the workplace, we, hence, use in the further course the DTM profiles of the used DTMs at the respondents' workplace. Therefore, we use covariance-based SEM to estimate the effect on technostress.

The Development of DTM Profiles

Theoretical Conceptualization

In order to build the foundation for our research, in a first step, we conducted a literature search. The focus was to identify DTM and their characteristics in relation to technostress (creators). To cover the full picture, the search additionally comprised literature of linked outcomes like stress and strain (including health and well-being). The list covered a broad picture of literature in different areas. Databases, namely EBSCO Business Source Premier, EBSCO Academic Search Premier, EBSCO Psych, Web of Science, and PubMed, were searched in the languages English and German. Because the seminal paper by Tarafdar et al. (2007) was published in 2007, only publications from this year onwards were included. The list of search strings is available in Appendix A.1. Types of publications that were considered are (academic) journals, reviews, proceedings, books, book chapters, and thesis. Overall, 273 articles relevant to our research were identified.

To enrich the insights from the literature research, we interviewed practitioners and experts. The semi-structured interview guideline included questions about technostress creators, technologies for which usage may cause stress, and DTM characteristics, which the subjects believed to cause stress and stressful usage behaviors. The complete interview guideline can be found in Appendix A.2. In total, 15 people participated in face-to-face interviews, including employee and employer representatives, experts from occupational health management, ethics, ergonomics, informatics, and human resource management. Each interview lasted between 30 and 90 minutes. The number of interviews was determined by content saturation, meaning interviews were conducted until no new aspects were identified and named by our experts. Interviews were audio-recorded, transcribed, and continuously analyzed through MAXQDA with a formalized coding strategy. Categories were built deductively because the interviews were structured in sections with questions concerning technologies, their characteristics, and how these exactly relate to technostress. These particular aspects guided the analysis to gain a better understanding of the relationship.

Following on from this, six focus groups were conducted (between 5 and 8 participants each) consisting of employees and managers from four different organizations (n=33). The groups covered different occupational groups and hierarchies. Participants were contacted by a responsible from the respective company and were asked to take part voluntarily. The groups almost got identical task descriptions to the experts. First, they named the technologies they use at the workplace and their characteristics. They rated which of these caused the most stress. Besides, they were asked for (short-term and long-term) consequences and successful strategies to cope with the stress. The guideline for the focus group workshop is available in Appendix A.3. The aim was to get insights from the practical perspective and collect examples for aspects that were named by our experts. All group discussions were recorded by an observer and the results documented in a picture protocol. Again, the results were written down, coded, and aggregated. For the technologies, for example, categories were identified when they named one specific software product (e.g., Edge as an example for an Internet browser).

The result of these steps is a conceptual understanding of nine characteristics of DTMs relating to technostress. See Table 1 for their definition. Please note that in a later quantitative pre-test, one characteristic (information provision) was split into two (push and pull). For brevity of presentation, Table 1 already shows this split. Simplicity of use refers to the characteristic complexity by Ayyagari et al. (2011). It was renamed to avoid confusion with the technostress creator techno-complexity (Ragu-Nathan et al. 2008). Reachability refers to the characteristic presenteeism by Ayyagari et al. (2011) and was renamed to avoid confusion with a common psychological phenomenon describing the feeling of obligation by employees to go to work even though they are ill.

Characteristic	Definition
Anonymity	Degree to which the use of a DTM stays anonymous and cannot be identified by others (in accordance with Ayyagari et al. (2011)).
Intangibility of Results	Degree to which results of the work with a DTM are immaterial in nature and therefore intangible (self-developed).
Mobility	Degree to which a DTM is usable independent of the location and enables to work from almost anywhere (self-developed).
Pace of Change	Degree to which a DTM changes dynamically and rapidly (in accordance with Ayyagari et al. (2011)).
Pull[6]	Degree to which information of a DTM is provided only on request (self-developed).
Push6	Degree to which a DTM automatically provides new information while using it (in accordance with Westermann et al. (2015)).
Reachability	Degree to which a DTM enables the individual to be contacted by third parties (in accordance with presenteeism in Ayyagari et al. (2011)).
Reliability	Degree to which a DTM works reliably and is free of errors and crashes (in accordance with Ayyagari et al. (2011)).
Simplicity of Use	Degree to which a DTM can be used without major effort or training (in accordance with complexity in Ayyagari et al. (2011)).
Usefulness	Degree to which a DTM supports the accomplishment of tasks and enhances job performance (in accordance with Ayyagari et al. (2011)).

Table 1: Characteristics of DTMs, their Source, and Definition

To sum up, we identified characteristics of DTMs that - according to literature and qualitative empirical research - relate to technostress. This answers RQ1.

Operationalization and Evaluation of Characteristics

For the development of scales for the characteristics of DTMs, we followed the guidelines of MacKenzie and Podsakoff (2011). Based on this, we collected items for already existing characteristics and further created items for newly identified characteristics resulting in the first draft of our scales. We created our items to be short and simple and use appropriate language for employees. During the development, we carefully made sure that the items only address one

[6] Please note that pull and push were first conceptualized as one characteristic with pull and push at opposite ends of the continuum. It was revised in later steps. Notifications may, only in some cases for some features, be configured by the user for certain technologies. Hence, individual settings of the users were not considered, and items were phrased with a general wording.

single aspect (i.e., no connection of different statements in one item) in order to prevent a confusion of the respondent. Thereby, we also considered recommendations proposed by Podsakoff et al. (2003) to avoid common method bias (CMB) by "improving scale items" (Podsakoff et al. 2003, p. 888). We used the anchor points of the existing rating scales to retain the interpretability and comparability of the results with the existing studies.

To evaluate content validity, we conducted a card-sorting via an online matching task with fellow researchers (n=39) in which they were asked to map items to characteristics (definition of the constructs) (Moore and Benbasat 1991). 85% correct matches were defined as the minimum boundary for the retainment of an item. Out of the 26 items, 22 were mapped correctly to the related construct by more than 85% of the persons, so we did not change them. The remaining four items were matched correctly by less than 85% of the participants. Thus, we changed the wording of these items to fit the corresponding construct better, provide more clarity, and reduce ambiguity. This step of item generation finished with the revised scales.

To evaluate the structure of our scales and validate our reworked items, we conducted a pretest. 445 respondents who were acquired via an online panel took part in the study. The data was collected anonymously as far as possible (some socio-demographic questions were included to evaluate the quality of the intended sample). Participants were instructed to respond honestly and gave informed consent to participation. This was done to further minimize common-method bias by "protecting respondent anonymity and reducing evaluation apprehension" (Podsakoff et al. 2003, p. 888). This principle was applied to all data collection processes. To get a better understanding of the participant's digital workplace, each respondent of our survey stated his or her usage of 40 technologies (Nüske et al. 2019), evaluated by 0 = "no usage", 1 = "monthly usage", 2 = "weekly usage", 3 = "daily usage", and 4 = "several times a day". The list of technologies included common hardware used at the workplace like a printer, laptop or stationary phone, software like text, table, and presentation programs, simulation programs, statistical and analysis tools, networks like cloud systems, intranet, wifi, and technologies like virtual augmented reality and mixed reality. Participants evaluated their perception regarding the characteristics of one randomly selected DTM that they used at least weekly. We decided to give each participant only one DTM to reduce dropouts due to the length of the survey.

We performed an EFA (parallel analysis revealed nine factors that were extracted using principal axis factoring with an oblimin rotation) to carefully assess the quality of our questionnaire and did a preliminary analysis of all scales. The result of this EFA properly reflected our assumption of the factor structure of the scales with nine underlying DTM characteristics. However, we faced some problems. First of all, we observed a few severe cross-loadings between the constructs simplicity of use and reliability. Also, we originally derived a bipolar construct "information provision" that contained aspects about how DTMs provide users with information distinguishing whether the information has to be requested explicitly by the user (pull) or whether they are provided automatically when available (push). Regarding the issues with the properties of the items of this characteristic, we decided to redefine it and created two separate scales for push and pull as they seem to be more than two ends of one construct. The two scales refer to the original settings of the technologies. Items were phrased with a general wording, that did not consider the individual settings of the user. In some cases, of course, it is possible to adjust the individual settings (e.g., turn off notifications on the lock screen of the smartphone) but this does not apply to all devices and features. In addition, organizational policies possibly interact with personal preferences (e.g., a user may be able to set his stationary telephone on mute, but he does not use this option because the supervisor expects him/her to be reachable on the phone for customers). Finally, we revised the items accordingly.

To evaluate and validate, we conducted a large-scale study distributing a questionnaire that, among other things, contained our scales on characteristics of DTMs. These were assessed with the same procedure as in the pre-test: each participant rated the characteristics of one randomly drawn DTM from the list of 40, which (s)he uses. To evaluate the respondent's technostress level, the items belonging to the five technostress creators introduced by Tarafdar et al. (2007) and Ragu-Nathan et al. (2008), namely techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty were included in the survey. This served the last step of our research to test for the influence of DTM profiles on technostress. We acquired respondents for the surveys via an external research panel focusing on German employees. Respondents were paid for participation in the study. We included control variables to review the representability of our sample. These comprised gender, employment status, occupational title and sector, number of hours worked per week, and education. The sample for the evaluation consisted of 4,560 respondents. The distribution of participants was representative of the German working population with respect to the control variables age, gender, and occupational sector.

We used a five-point Likert rating scale from 0 = "I do not agree at all" to 4 = "I totally agree" to measure the technostress creators and the characteristics of DTM. All questions were in German. If necessary, the items were translated. Therefore, multiple German native speakers translated the questions in parallel. They met afterward to resolve discrepancies and agree on the most suiting translation. For more detailed information about the final scales used in this study and their sources, see Appendix A.4. For a list of the technologies, see Appendix A.5.

As the EFA in the pre-test showed few severe cross-loadings, we reinvestigated the factor structure with an EFA in the data set of the main study. Therefore, we split our study population into two evenly large subsets. On the first subset (n=2,280), we performed the EFA (parallel analysis revealed ten factors that were extracted using principal axis factoring with an oblimin rotation). This time no problematic cross-loadings of the items on a competing construct were observed. For more detailed information on the results of this EFA see Appendix A.6. Following the EFA, we performed a CFA on the second subset (n=2,280) with maximum likelihood estimation of fifteen latent factors (ten characteristics of DTMs, five technostress creators) that were allowed to intercorrelate in the model to analyze our measurement model further. The descriptive statistics, item reliabilities, and internal consistency are presented in Table 2.

Construct	No. of Items	Mean	Standard Deviation	Loadings	Cronbach's α	AVE
Anonymity	4	1.78	1.10	0.76-0.92	0.89	0.82
Intangibility of Results	6	1.58	1.10	0.60-0.90	0.92	0.80
Mobility	5	2.55	1.27	0.76-0.93	0.93	0.85
Pace of Change	4	1.78	1.15	0.92-0.94	0.96	0.93
Pull	3	2.47	1.00	0.74-0.89	0.83	0.80
Push	3	2.07	1.17	0.75-0.85	0.85	0.81
Reachability	4	2.71	1.24	0.92-0.95	0.97	0.94
Reliability	3	2.92	0.89	0.86-0.93	0.93	0.90
Simplicity of Use	3	3.13	0.89	0.81-0.92	0.90	0.87
Usefulness	4	2.81	1.05	0.82-0.90	0.92	0.86
Techno-Complexity	5	1.23	1.23	0.81-0.88	0.90	0.71
Techno-Insecurity	4	1.24	1.29	0.78-0.86	0.83	0.66
Techno-Invasion	3	1.28	1.35	0.75-0.90	0.80	0.72
Techno-Overload	4	1.63	1.30	0.79-0.90	0.88	0.74
Techno-Uncertainty	4	1.81	1.23	0.81-0.88	0.87	0.72

Notes: Descriptive Statistics, Item Reliabilities, Internal Consistency, and AVE

Table 2: Statistical Quality of the Measures used in the Study

All loadings of the items on their respective latent factors in the CFA were above the value of 0.71, which indicates that more than 50 % of the variance of this item is explained by the underlying construct. Only for the intangibility of results, lower loadings were observed. However, since the average variance extracted (AVE) of intangibility of results (and for all other constructs) was above 0.50, we did not consider it critical and retained the indicators. Cronbach's Alpha showed values of at least 0.80 for all scales indicating internal consistency.

In the next step, we assessed discriminant validity based on the Fornell-Larcker criterion (Fornell and Larcker 1981) as Cronbach's Alpha relies on correlations of the items and, thus, does not account for dimensionality of constructs. The Fornell-Larcker criterion compares the size of the correlations of the latent constructs to the AVE. The square root of each construct's AVE was higher than the correlations with the other constructs (see Table 36 in Appendix A.7). Another, newer criterion to asses discriminant validity is the heterotrait-monotrait ratio introduced by Henseler et al. (2015). It sets the average correlation of items measuring different constructs (heterotrait-heteromethod) in relation to the average correlations of items measuring the same construct (monotrait-heteromethod). If the indicators of one construct correlate higher with each other than with the indicators of different constructs, the ratios should be small. Ratios close to 1 indicate a lack of discriminant validity. The ratios were obtained for the characteristics of DTMs and the technostress creators as they are used in the model to analyze for our second research question. All ratios were below 0.85, indicating that discriminant validity is good. For more detailed information on the results, see see Table 36 in Appendix A.7. Overall, we consider discriminant validity as given.

In the last step of validating our measurement instrument, we evaluated the fit of our model to gain further information about our assumptions on the data structure. The fit was judged according to the following guidelines: The root mean square error of approximation (RMSEA) indicates good model fit at values smaller than 0.6. The square root mean residual (SRMR) should show values smaller than 0.05. Comparative fit index (CFI) and Tucker-Lewis index (TLI) indicate a satisfactory model fit if they are higher than 0.90 and good fit at values above 0.95. We did not consider chi-square for the evaluation of the model fit, because the indicator has shown to be sensible to sample size in simulation studies (Boomsma 1982). For our model, CFI (0.956) and TLI (0.951) were above 0.95, indicating good fit of the initial model with ten latent, correlating characteristics. Both SRMR (0.036) and RMSEA (0.044) showed only small deviations of the estimated from the expected covariance matrix with values below 0.05 and/or 0.06, respectively. Therefore, we argue that we finally validated our measurement model. To sum up, we now have validated measurement scales for the identified characteristics of DTMs that - according to literature and qualitative empirical research - relate to technostress.

To confirm this ten-factor structure, a nested model comparison was conducted. The simpler model comprised nine latent factors (interim result from the first EFA in pre-test, reapplied to data from the main study) where all items of the two factors simplicity of use and reliability loaded on the same, common construct. A chi-square difference test revealed significant better fit ($\chi^2_{Model1} = 5277.18$, $\chi^2_{Model2} = 3327.98$, $df_{Model1} = 651$, $df_{Model2} = 657$, $\Delta\chi^2 = -1949.20$) of the model with ten latent factors. The fit indices are displayed in Table 3.

Model	CFI	TLI	RMSEA	SRMR
Nine Factors – Model 1	0.924	0.914	0.059	0.041
Ten Factors – Model 2	0.956	0.951	0.044	0.036

Table 3: Nested-Model Comparison of the Measurement Model

Profiles of DTMs Based on their Characteristics

To get a better understanding of the differences between technologies with respect to their characteristics, we created a profile for each of the 40 DTMs from our list. Each profile line consists of the means of all ten characteristics that were evaluated for this one specific DTM . We argue that the characteristic of a DTM that is used more frequently has a higher impact on the overall perceived characteristics of DTMs. Therefore, we only regarded the responses of persons that used this specific DTM at least once a day. We then calculated a mean score for the ten characteristics. See Table 4 for examples.

From the overall list of 40 technologies, some had to be excluded for the profiles. Due to the randomized choice which DTM the respondent was asked to evaluate, group sizes were in some cases below 30. These were considered too small to provide unbiased information. For example, 86 used augmented, virtual and mixed reality daily, but only ten respondents were asked to evaluate its characteristics due to the randomized sampling. All profiles with means and standard deviations are provided in Table 4. The table shows how different technologies are perceived by users. It is important to note that these perceptions are from users, that is, they are conditional on the respondent working in a job where the employer assumes a task-technology fit and, thus, provides the DTM. Cash systems have a higher perceived usefulness than statistics software to pick just one example. Likely, only few people use both types of systems. The perceptions originate from different people in different jobs. Five profiles are visually displayed to highlight similarities and differences. For example, smartphones enable mobile working represented by high values of mobility. The same applies to e-mails because usually, these can be checked on the run with the smartphone. However, in contrast to smartphones, e-mails have a rather low pace of change. A new smartphone is released almost every other week by different companies, whereas the functionality of the e-mail program remains the same as ten years ago (Figure 7).

To sum up, we now have profiles of the 26 most important (i.e., common and frequently used) workplace technologies along with the characteristics that — according to literature and qualitative empirical research — relate to technostress. This answers RQ2.

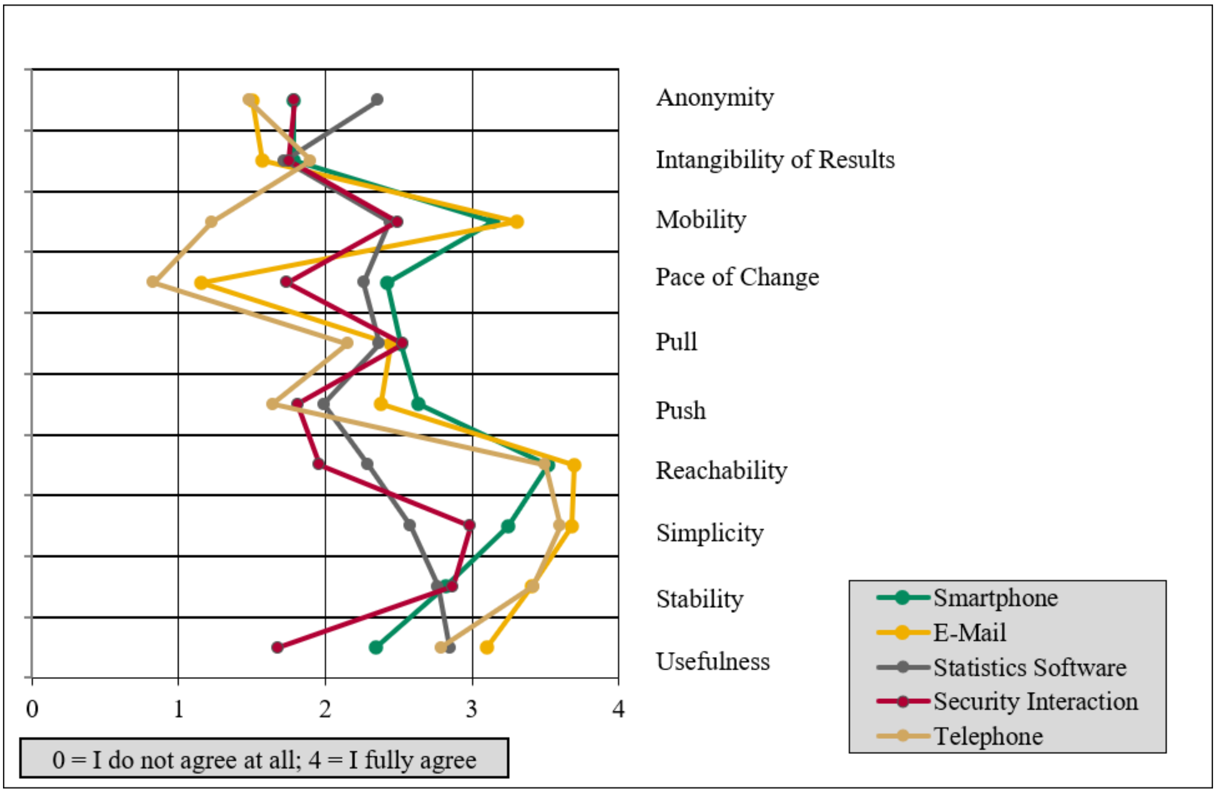


Figure 7: Profiles of Five Different DTMs Based on their Characteristics

Technology	n	Usefulness		Simplicity of Use		Reliability		Anony-mity		Mobility		Reach-ability		Pace of Change		Pull		Push		Intangi-bility	
		M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Administrative Software	69	3.02	0.98	2.79	1.00	2.82	0.89	1.50	1.15	2.18	1.39	2.19	1.34	1.90	1.01	2.47	1.20	1.71	1.15	1.38	1.13
Cash System	41	3.08	1.10	3.49	0.73	3.19	0.73	1.80	1.39	2.14	1.68	1.37	1.57	1.53	1.38	2.46	1.37	1.69	1.53	1.64	1.50
Cloud Computing	54	2.60	1.04	2.73	1.01	2.44	1.03	1.64	1.13	2.88	1.16	2.53	1.25	2.16	0.96	2.49	1.16	1.97	1.22	1.66	1.17
Database	134	2.86	1.05	2.60	1.04	2.71	0.96	1.61	1.16	2.15	1.37	1.92	1.32	1.88	1.09	2.44	1.18	1.92	1.29	1.46	1.22
E-Mail	311	3.10	1.07	3.68	0.68	3.41	0.72	1.50	1.27	3.31	1.21	3.70	0.62	1.15	1.14	2.45	1.31	2.38	1.38	1.57	1.32
Headset	69	2.89	1.17	3.35	0.98	3.16	1.00	1.78	1.45	2.32	1.48	2.97	1.18	1.18	1.28	1.75	1.41	1.69	1.39	1.83	1.35
Internet	220	3.10	0.97	3.42	0.76	2.88	0.84	1.86	1.22	3.25	1.06	3.22	0.95	2.10	1.07	2.61	1.10	2.10	1.20	1.65	1.12
Knowledge Management	91	2.86	1.07	2.92	1.05	2.70	1.00	1.91	1.28	2.55	1.33	2.36	1.25	2.21	1.08	2.54	1.12	1.86	1.22	1.68	1.19
Laptop	125	3.07	1.15	3.55	0.74	3.29	0.78	1.79	1.28	3.23	1.15	3.03	1.07	1.73	1.18	2.65	1.10	2.06	1.30	1.23	1.23
Logistics System	33	3.05	0.91	2.94	0.95	2.65	1.00	1.92	1.23	1.96	1.45	1.86	1.42	2.04	1.28	2.60	1.09	1.99	1.31	1.45	1.33
Management Information Software	42	2.66	0.99	2.60	0.88	2.62	0.89	1.69	1.36	2.53	1.25	2.53	1.29	2.40	1.06	2.64	1.12	1.91	1.38	1.65	1.40
Mobile Phone	62	2.35	1.37	3.46	0.97	2.98	1.18	1.75	1.35	2.79	1.46	3.54	0.80	1.15	1.20	2.23	1.24	1.88	1.39	2.10	1.13
Network Hardware	82	2.78	1.07	2.69	0.95	2.56	0.94	1.58	1.16	2.55	1.29	3.01	1.03	2.07	1.07	2.35	1.12	1.93	1.26	1.58	1.13
Office Software	188	3.33	0.85	3.09	0.91	3.12	0.86	1.95	1.21	2.98	1.22	1.83	1.37	1.64	1.15	2.13	1.23	1.45	1.30	1.21	1.27
PC	301	3.17	1.04	3.27	0.85	3.01	0.85	1.51	1.23	1.48	1.52	2.92	1.13	1.80	1.20	2.64	1.10	1.98	1.32	1.33	1.20
Printer	303	3.25	0.96	3.57	0.70	3.24	0.82	1.74	1.35	1.87	1.57	2.39	1.47	1.27	1.19	2.20	1.34	1.72	1.44	1.07	1.21
Production Planning	30	2.77	1.14	2.46	0.98	2.46	1.09	1.75	1.26	1.91	1.43	1.73	1.30	1.70	1.28	2.34	1.30	1.71	1.37	1.81	1.24
Realtime Communication	50	2.89	1.11	3.19	1.00	2.84	1.08	1.81	1.38	2.68	1.44	3.22	0.89	2.05	1.15	2.46	1.16	2.41	1.30	1.94	1.18
Security Background	94	2.18	1.28	2.55	1.02	2.79	0.94	2.00	1.11	2.93	1.18	2.13	1.27	1.94	1.19	2.39	1.16	2.12	1.24	2.08	1.27
Security Interaction	150	1.68	1.30	2.99	1.00	2.87	0.91	1.79	1.23	2.49	1.37	1.96	1.36	1.74	1.29	2.53	1.14	1.81	1.29	1.75	1.25
Smartphone	151	2.56	1.26	3.25	0.92	2.91	0.95	1.74	1.14	3.16	1.13	3.55	0.81	2.37	1.08	2.56	1.15	2.32	1.26	1.78	1.24
Social Collaboration	71	2.46	1.14	2.77	0.92	2.27	1.00	1.63	1.12	2.93	1.09	3.19	0.87	2.19	0.99	2.38	1.05	2.32	1.15	2.03	1.06
Statistics Software	32	2.85	0.96	2.58	0.99	2.77	1.00	2.36	1.23	2.44	1.32	2.29	1.35	2.26	1.08	2.37	0.98	1.99	1.29	1.72	1.42
Tablet	58	2.68	1.29	3.47	0.87	2.81	1.14	1.73	1.25	3.09	1.21	2.76	1.32	1.83	1.27	2.64	1.24	2.15	1.40	1.69	1.40
Telephone	246	2.79	1.14	3.60	0.75	3.42	0.81	1.48	1.40	1.23	1.53	3.50	0.82	0.83	1.16	2.15	1.38	1.64	1.45	1.90	1.37
Wireless Network	164	2.94	1.13	3.21	0.90	2.74	0.92	1.91	1.22	2.85	1.23	3.34	0.85	2.01	1.17	2.49	1.17	2.29	1.23	1.64	1.26

Notes: Mean and standard deviation for each characteristic for each DTM; we do not provide a characteristics profile for content management systems, creative- and design-software, medical software, augmented, virtual and mixed reality, digital cash flows systems, sensory systems, artificial intelligence, automatic productions systems, e-commerce systems, product/software development tools, voice interaction technologies, systems for localization and distance determination, and simulation/ modelling software ($n < 30$).

Table 4: Profiles of Digital Technologies

The Influence of DTM Profiles on Technostress

Technostress at work arises from a workers' interaction with typically a range of DTMs. It does not depend on a single DTM but on the portfolio of DTMs at the workplace and their characteristics profiles. Thus, in order to investigate the influence of DTM profiles on technostress, we aggregated the profiles of the DTMs to digital workplace portfolios. For example, for a respondent who uses a smartphone, laptop, E-Mails, social collaboration software, and wireless networks for work, we took the characteristic profiles of these five DTMs and averaged them to build one mean "portfolio" score across the five DTMs for each of the ten characteristics.

We set up a covariance-based SEM to measure the influence of the ten characteristics of the DTM portfolio at the workplace on the five technostress creators techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty (Ragu-Nathan et al. 2008; Tarafdar et al. 2007). We conducted Harman‘s single factor test, which showed that about 11 % is the highest proportion of variance attributed to one factor, which suggests that common-method bias is not a problem. Next, we statistically controlled for common-method bias by modeling a method factor (Podsakoff et al. 2003). The comparison of the results of the structural model with and without method factor showed no substantial differences (ΔCFI = 0,029). Researchers (Cheung and Rensvold 2002; Little 1997) have suggested that differences in the CFI less than .05 are acceptable and indicate the equivalence of measurement models. Thus, common-method bias seems not to be a major concern for our data. The model showed good fit to the data (CFI = 0.972, TLI = 0.962, SRMR = 0.031, RMSEA = 0.036).

Hypotheses were tested two-tailed because we did not have specific directional hypotheses about the influence of the characteristics of the digital workplace on technostress. Table 5 displays the results. For a detailed list of all paths and their respective *t*-statistics, including the *p*-values see Appendix A.8.

Characteristic \ TS Creator	Techno-Complexity	Techno-Insecurity	Techno-Invasion	Techno-Overload	Techno-Uncertainty
Anonymity	-0.16**	-0.27**	-0.40***	-0.10	-0.17
Intangibility of Results	+0.16**	+0.34***	+0.31***	+0.25***	+0.30***
Mobility	+0.08	+0.18***	+0.28***	+0.12**	+0.14**
Pace of Change	-0.04	+0.04	+0.31***	+0.10	+0.07
Pull	-0.16	-0.18	-0.40**	-0.23	-0.17
Push	+0.11	-0.08	-0.28**	-0.14	+0.03
Reachability	-0.20*	-0.16	-0.18*	-0.13	-0.17*
Reliability	-0.18	-0.25	-0.46**	-0.07	+0.11
Simplicity	+0.08	-0.19	+0.40*	-0.18	-0.50**
Usefulness	+0.00	+0.22**	+0.14	+0.11	+0.07
R^2	0.11	0.20	0.22	0.12	0.16

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; '+' indicates that a higher value of the characteristic within the digital work

Table 5: Influence of the Digital Workplace Portfolio on Technostress Creators

In this final step of the analysis, we answer RQ3, which asked how the profiles of DTMs used at the workplace influence technostress. Results of the structural model reveal that not all portfolios of characteristics at the digital workplace influence technostress in the same manner, but each of the characteristics is significantly linked to at least one technostress creator.

Discussion and Conclusion

We investigated the characteristics of DTMs that are related to technostress. Therefore, we did a literature search and qualitative interviews in order to expand the understanding of characteristics that have previously been presented in the literature. To validate the characteristics as well as their relationship with technostress, we conducted a quantitative survey study. We used structural equation modelling to reveal the characteristics' relationship with technostress creators. The results answer our three research questions by showing the existence of ten characteristics of DTMs related to technostress, profiling 26 common workplace technologies along the ten characteristics, and relating the digital workplace portfolio with technostress creators.

In terms of revealing characteristics of DTMs with relation to technostress creators, we found evidence for ten different characteristics. Each DTM characteristic relates to at least one technostress creator and each technostress creator to at least two characteristics.

In this dense web of relationships, we found that anonymity is negatively related to complexity, insecurity, and invasion. For insecurity, for example, this means that if the users may use their technologies anonymously without leaving traces of their usage behavior, employees fear to lose their jobs less as they less feel their work activities to be monitored. Intangibility of results is positively associated with all five technostress creators. Again, for insecurity, this relationship is understandable as employees experience more fear of losing their jobs if they do not see the results of their work and thereby feel no progress in accomplishing their tasks. Regarding these two results concerning insecurity in combination this could be interpreted in the following way: With high intangibility of results, employees might experience a lack of productivity and they fear losing their job because this seemingly poor performance could be controlled or traced, for example by the supervisor, if a system does not allow anonymous usage. For mobility, we found positive relations with insecurity, invasion, overload, and uncertainty. With regard to invasion, this may be because mobile workplaces allow individuals for more flexibility in doing their tasks. Therefore, they may experience a stronger feeling of blurring boundaries between job and private life, resulting in higher levels of perceived invasion. Pace of change is only related to invasion and the relationship is positive, meaning that a high pace of change increases the feeling of one's life being invaded with DTMs. This may be because employees have to use their non-work times (e.g. weekends) in order to deal with the newly changed DTMs and learn how to use them and, thus, feel their private lives as being invaded by DTMs. In contrast to pace of change, pull as well as push is negatively linked with invasion. For pull, this relationship may be because individuals actively have to access information via their digital workplace portfolio and, thus, are more in control of when they want to do so. For push, however, in the first sense, one would expect a positive link to invasion. But we argue that, if individuals know that their DTMs will notify the individuals about important work issues, they do not have to constantly check their smartphone or other DTMs for important updates and, thus, can mentally disconnect from their job when being with their family. Reachability is negatively associated with complexity, invasion, and uncertainty. One possible interpretation of the decreasing uncertainty could be that people who are well reachable (i.e. due to their position) will inevitably interact and deal with the DTM permanently, which means that they have little uncertainty in using it. For reliability, we only found a negative relation to invasion. Simplicity is linked with invasion and uncertainty. For invasion, the relation is positive, whereas, for uncertainty, it is negative. Interestingly, simplicity does not affect complexity. Lastly and unexpectedly, usefulness is positively related to insecurity. At this point, further research is needed to better understand and interpret the relationship.

The research in this section contributes to theory in several ways. The first contribution is the identification and definition of further characteristics of DTMs that affect technostress at an individual’s workplace, including measurement scales for the newly added characteristics. Placing these newly identified characteristics side by side with the ones from extant literature (esp. from Ayyagari et al. 2011), our research presents the most holistic set of DTM characteristics related to technostress. Further, to the best of our knowledge, we are the first to combine the characteristics of Ayyagari et al. (2011) with the technostress creators of Ragu-Nathan et al. (2008) and thereby can show their relationships. With this broader understanding of characteristics, future research can investigate the influence of digitalization on technostress in more detail.

Second, we show that it is important to investigate the workplace as a whole based on the portfolio of technologies at the workplace. Prior research either investigates individual technologies (e.g. Hung et al. 2015; Maier et al. 2015; Salo et al. 2019) or the entire digital workplace without considering the individual technologies at work (e.g. Ragu-Nathan et al. 2008; Tarafdar et al. 2007). We take an intermediate way considering all major individual DTMs at the workplace. We build DTM profiles on the individuals’ perception of characteristics and not by asking DTM experts. Stress is a construct that builds on the perception of a situation and the individual’s own ability to cope with a certain situation. Therefore, from the individual’s point of view, the perceived characteristics of DTMs at the workplace are key because stress is neither solely anchored in the environment and its demands nor solely in the person characteristics (Folkman and Lazarus 1984). Asking users rather than design experts seems appropriate according to adaptive structuration theory (DeSanctis and Poole 1994). Outcomes of the use of advanced DTM do not only depend on the structure of the DTM but also the social interaction of the user with the DTM (which can be different than intended by the designer also depending on the organizational practices and norms). These profiles were put together to an individual portfolio consisting the mean characteristics of the different DTM each employee uses at his/her own workplace. This provides a more holistic picture than looking at only a single DTM; further, it allows to trace the effects on technostress back to characteristics and from there to individual DTMs rather than considering DTMs at the workplace as monolithic.

Third and last, we give evidence on the relationship of the characteristics with different technostress creators instead of technostress in general. This more detailed understanding can help future research to develop specific preventive measures and coping strategies for concrete technostress creators at concrete workplaces. In sum, the identification and measurement of characteristics of DTMs along with knowledge on their effect on technostress enable future research to cluster technologies and evaluate different technologies and workplaces based on their impact on technostress. Future research could consider whether the DTM profiles prove to be consistent among demographic and cultural differences. Also, the size of the DTM profile combined with the intensity of usage or additional moderating characteristics influencing technostress can be analyzed.

The results of this study also provide implications for practice. Since prior research has shown the negative effects of technostress, including lower productivity and lower job satisfaction, organizations should aim to prevent and lower the level of technostress of their employees. Based on our developed items for characteristics of DTMs, digital workplaces can be evaluated on their possible susceptibility to technostress, by for example identifying technologies that outshine the positive characteristics of other DTMs in terms of technostress. This is important as we were able to show that the combination of technologies and their aggregated mean characteristics are associated with technostress creators. The combination of technologies matters as one DTM with its' characteristics can distort the overall sensation and lead to technostress.

Workplace designers should focus on usability features, including usefulness, simplicity of use, and reliability, but also on technologies that enable mobility and pull configurations. When individual technostress creators are of specific concern for a given workplace or company, the guidance becomes more nuanced on which characteristics to look out for and which technologies have a favorable profile regarding these characteristics. Besides, individuals can affect their levels of technostress by adjusting their workplace technologies. Therefore, employers also should give their employees the flexibility of configuring their DTMs in a way that is most beneficial for each individual.

However, there are limitations to our research. Each respondent to the survey assessed only the characteristics of one DTM and not the characteristics of the DTMs at her or his entire workplace. However, since our sample is of a high number, we were able to assign the perception of the characteristics between subjects.

Despite these limitations, our results add to a broader understanding of characteristics of DTMs at an individual's workplace, not only by extending the number of characteristics that were already known but also by revealing the structure among them as well as their effect on technostress creators.

3.2. Analyzing the Effect of Autonomy Features

After the previous section examined the characteristics of DTM and their influence on employees' health, the remainder of this section examines features, i.e., the functionality afforded by DTM, in more detail and how they affect performance and well-being. The research activity does not focus exclusively on the working context but also addresses the private context, which is also undergoing a change as a result of digitalization. This change affects, for example, the way we work, how we communicate, but also how we learn and evolve. As a result, personal analytics is one of the major new trends included in Gartner Hype Cycles for Emerging Technologies (Walker 2017). Personal analytics describes an individual's use of data for purposes such as healthcare and self-actualization. It mostly makes use of DTMs for real-time measurement of data regarding goals, activities, and behaviors (Lupton 2014a). Positive technologies, as a subset of such digital self-tracking technologies - aim to support users in achieving their goals (Botella et al. 2012) and in increasing their productivity, the realization of which results in improved well-being (Harkin et al. 2016; Klug and Maier 2015), another core aim of positive technologies.

A crucial process for attaining a goal is the monitoring of the goal-pursuing activities which helps to ensure that initially-set goals are translated into action (Harkin et al. 2016). A meta-analysis on monitoring goal progress revealed that progress monitoring has more substantial effects on goal attainment when the progress is recorded and the frequency of progress monitoring is increased (Harkin et al. 2016). Self-tracking DTM can support this by providing capabilities to monitor the user's goal progress. So-called habit trackers, mostly available as mobile applications, enable users to set goals and easily keep track of the goal progress by providing a stimulating but straightforward design. Loop Habit Tracker, for example, is one of the best-rated habit trackers in the Google Play Store and provides users with a simple and easy-to-use interface to keep track of their goals.

However, it requires more than an easy-to-use interface so that a habit tracker is used continuously (Buchwald et al. 2018; Pinder et al. 2018). Imagine coming home late from work, exhausted from the day. Your self-tracking DTM tells you that you still have a run scheduled for today according to a plan that you committed to a few weeks ago. If you do not run today, you will not reach your goal and feel bad for it. You might even question your motives for committing to your plan in the first place. Even if you do run today, it may bring you closer to your goal, but it is not clear whether this will increase your well-being. What if your plan and your self-tracking DTM allowed you to easily adapt your behavior to the circumstances? After all, you could have moved the run to a rest day scheduled for yesterday or tomorrow. It might help here if habit trackers not only allowed freedom in the planning stages but also during the execution of the plan and progress tracking.

Furthermore, providing the possibility to adapt the technology and, in particular, the pre-determined plans to meet the user's needs would also foster the continuous usage of the habit tracker (Buchwald et al. 2018; Pinder et al. 2018). This means that affording users with certain kinds of autonomy while they work towards their goals, which could have a tremendous effect on the success in pursuing goals as well as well-being (Patall et al. 2008; Ryan and Deci 2000). Such a possibility for autonomy is an affordance. An affordance, in general, is defined as "the possibility for goal-oriented actions afforded to specific user groups by technical objects" (Markus and Silver 2008). We define an autonomy affordance in the context of self-tracking DTM as the possibility to continuously adapt the self-tracking DTM and its comprised information to the user's needs. However, most habit trackers mainly focus on an appealing design or a wide selection of features (Zhao et al. 2016) and neglect the potential positive effects of providing autonomy affordance by making a self-tracking DTM more adaptable to the user's needs (Pinder et al. 2018). From this we derive the following RQ:

RQ) What is the influence of the provision of enhanced autonomy affordance and its actualization in self-tracking DTM on goal performance and well-being?

In the following, we describe the essential components of our research question which are concepts that are discussed in various areas of research such as the DTM design, self-tracking, positive computing, and psychology. Based on this, we derive hypotheses from explaining the relationship between our constructs. Subsequently, we describe the development and deployment of the self-developed self-tracking DTM for the data collection. After the presentation and discussion of our results, we cover our work’s theoretical and practical implications, its limitations, and the resulting need for further research.

Theoretical Background

Self-tracking DTM can be employed to increase individuals' well-being and support them, for example, in achieving their goals. These DTM are designed with the aim of “improving the quality of our personal experience with the goal of increasing wellness and generating strengths and resilience in individuals, organizations, and society” (Botella et al. 2012). For this purpose, various types of data (e.g., biological, physical, behavioral, or environmental information) are collected within the DTM, both manually or by using further DTMs such as mobile devices and sensors. This enables an increasingly detailed real-time measurement of data regarding activities and behaviors and their analysis and distribution (Lupton 2014b).

A goal can be defined as “a cognitive representation of a future object that an organism is committed to approach or avoid” (Elliot and Niesta 2009). In the context of self-tracking, goals like doing sports, getting up early, or eating in specific ways may refer to behaviors which the individual aims to transform into habits. “Habits are learned dispositions to repeat past responses” (Wood and Neal 2007), i.e., behaviors or actions which are automatically triggered by cues in the individual’s context. Goals play an essential role in habit formation as they provide the trigger to perform the first repetitions of the desired behavior which then becomes automatic (Wood and Neal 2007). Goals can furthermore be distinguished regarding their time horizon. Long-term goals take more than five years, medium-term goals take one to five years (Steca et al. 2016), and short-term goals take up to one year to achieve (Boersma et al. 2006).

Once a goal is set, there are multiple terms for describing the path to its fulfillment as well as its fulfillment itself. In a broad literature review related to goal progress, Klug and Maier (2015) include studies assessing goal progress, goal pursuit, goal attainment, and goal achievement, and subsume the terms under goal success. In a literature review related to monitoring goal progress, Harkin et al. (2016) distinguish between behavioral goal performance and goal attainment. As self-tracking centers on gathering and analyzing data about regular habits, behaviors, and feelings (Lupton 2014a), and as the behavior of individuals is the basis for any determination of goal success, we will use the term goal performance to describe the process of pursuing and possibly accomplishing a goal.

A major driver of goal performance is motivation. According to Ryan and Deci's Organismic Integration Theory, motivation can be subdivided concerning the degree of internalization, which is the extent to which an individual incorporates a value or a behavior's regulation into the self (Ryan and Deci 2000). In three studies and a meta-analysis, Koestner et al. (2008) found higher internalization to be substantially related to goal progress, whereas lower internalization was not.

Goal performance has furthermore been linked to enhanced well-being in various studies (Ryan and Deci 2001). The psychological literature regarding well-being can be divided into two main fields: subjective well-being and psychological well-being (Hall 2015). To determine the over-all flourishing of an individual, both need to be considered (Huppert and So 2009). Subjective well-being takes a hedonic perspective, i.e., it focuses on happiness and positive or negative, temporary feelings. Psychological well-being takes an eudemonic view, i.e., it concentrates on self-attainment and meaning (Ryan and Deci 2001).

Moreover, according to Ryan and Deci's Self-determination Theory, the three basic needs autonomy, competence, and relatedness are crucial for promoting well-being (Ryan and Deci 2000). The drivers of autonomy are "a sense of choice, volition, and freedom from excessive external pressure" (Ryan and Deci 2000). Transferred to the context of monitoring goal performance in self-tracking IS, users experience autonomy if provided with options to adapt their plans and exercise control regarding their goal-directed behavior.

We take an affordance perspective on the interplay of the provision of these options in self-tracking DTM and their perception and actualization by the users. A functional affordance, in general, is defined as "the possibility for goal-oriented actions afforded to specific user groups by technical objects". In the context of our work, users of self-tracking DTM (user group and technical object) aim to achieve and track progress regarding goal performance (goal). An affordance arises from the relationship between the properties of an object and the abilities of the agent who interacts with it. It is not a property or feature of the object per se (Norman 2013). Following Norman (2013), an affordance is communicated by signifiers, which refer to "any mark or sound, any perceivable indicator that communicates appropriate behavior to a person". We define and use the term autonomy affordance as the possibility to adapt users' plans for goal-directed behavior, which is enabled by features and communicated by signifiers in a self-tracking DTM.

Hypotheses Development

According to Self-determination Theory, higher levels of autonomy should result in higher levels of well-being (Ryan and Deci 2000). In this study, we focus on the subjective well-being facet as it is more variable over time (Diener et al. 2006; Krueger and Schkade 2008). In contrast to the more stable psychological well-being, we can observe the effects of a manipulation of autonomy affordance on subjective well-being in the course of a field experiment.

> *H1: We hypothesize that an enhancement of autonomy affordance positively affects subjective well-being.*

This enhancement of autonomy affordance is manifested as the extension of features (and their signifiers) that enable plan adaptations for the goal-directed behavior of self-tracking DTM users. An affordance can exist without being actualized (Strong et al. 2014). H1 covers the mere offer of enhanced autonomy affordance and its relationship to subjective well-being. We suggest that it is enough for users of a self-tracking DTM to perceive enhanced autonomy affordance by its signifiers to feel more autonomous.

In case that autonomy affordance is actualized, its actualization (a behavior) should self-evidently be contingent on its provision.

> *H2: We thus hypothesize a positive effect of the enhancement of autonomy affordance on its actualization.*

As pointed out in H1, self-tracking DTM users should feel more autonomous by simply perceiving enhanced autonomy affordance. Besides, we suppose that the positive effect of the experience of autonomy on subjective well-being in part works via the mediator affordance actualization.

> *H3: We hypothesize that the actualization of autonomy affordance positively influences subjective well-being.*

In a meta-analysis of studies examining choice and its various outcomes, Patall et al. (2008) found significant, mainly positive effects of choice on, among others, effort, task performance, and subsequent learning. Other studies as well showed that the satisfaction of the basic need autonomy, among others, was positively related to learning outcomes (Akbari et al. 2015).

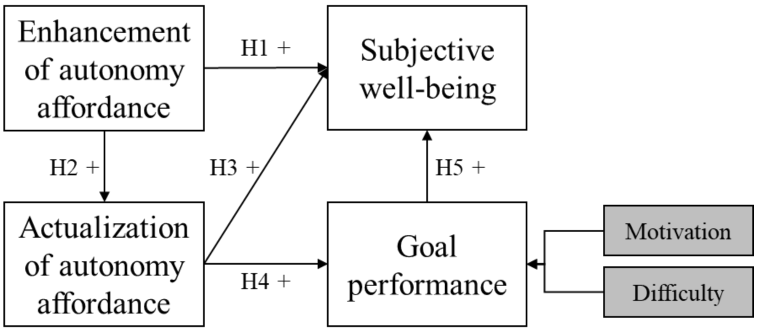
> *H4: Transferred to our context, we hypothesize that the actualization of autonomy affordance positively affects goal performance.*

Goal performance has been linked to well-being in several studies. Brunstein (1993) found progress in the achievement of personal goals to predict subjective well-being. Two meta-analyses confirmed the high correlation between successful striving towards long-term goals and subjective well-being (Klug and Maier 2015; Koestner et al. 2002). Steca et al. (2016) found a slightly weaker positive influence of short-term goal progress on subjective well-being.

H5: We hypothesize goal performance to positively affect subjective well-being.

When examining the effect of enhanced autonomy affordance and its actualization on goal performance and well-being in self-tracking DTM, two influences external to self-tracking should be controlled: motivation and difficulty. Vansteenkiste et al. (2004) showed intrinsic goal-motivation as well as autonomy-supportive environments to have an impact on the performance of students. We cover the latter influence, autonomy-supportive contexts, with our main independent variable, enhanced autonomy affordance. However, we do not yet consider the former influence, motivation. Thus, we include a goal's original motivation as a control variable.

Lastly, performing well concerning goals that are easy to achieve seems to be more likely than concerning harder or more complicated goals. As a second control variable of goal performance, we, therefore, include goal difficulty in our model. Figure 8 outlines the proposed relationships between our four focal constructs and the two control variables.



Notes: Hypothesized relationships between enhanced autonomy affordance, its actualization, subjec-tive well-being, goal performance, and the control variables

Figure 8: Research Model and Developed Hypotheses

Methodology

The empirical test of the hypothesized relationships bases on a field experiment manipulating autonomy affordance to measure the effects. As no self-tracking DTM allowing to manipulate autonomy affordance was readily available, we designed, developed, and deployed a mobile application for tracking the goal performance of individuals regarding self-set goals. Participants were randomly assigned to either of two treatments differing in the level of autonomy affordance. Data was gathered automatically by the app.

The Measurement Instrument

The mobile application developed to allow for testing our hypotheses was available for the operating systems Android and iOS. The app enabled users to enter goals that they wanted to achieve or habits that they wanted to integrate into their life. On one tab ("GOALS"), users could create and manage goals. To create a goal, users entered a title or selected one from a list of 90 recommendations from different categories such as sports and learning. Users were then asked to indicate the weekdays on which they would like to conduct activities pursuing the new goal. Users were asked to state the subjective difficulty of reaching the new goal and to select the most suitable motivation for the new goal from a list. Users were also able to add further goals, edit, or delete existing goals.

In a second tab ("JOURNAL"), users could view their goal journal. The view provided a list divided into separate days which were displayed in the headline of each section, starting one week before the current day and ending three weeks after. Under each headline, all goal-pursuing activities of all goals which were planned for that day were listed and identified via the goal title. For each of these activities, users could log their progress by clicking on a check (done) or on a cross (not done). In each case, they were asked to indicate their current feeling on a scale of five emoji. Logging and unlogging activities were enabled for the current day and all days before.

For illustrations of the measurement instrument, please see Figure 9 and Appendix B.1.

Manipulating Autonomy Affordance

We created two versions of the app which differed regarding the level of autonomy affordance. We manipulated autonomy affordance by including or excluding a total of three features and three autonomy affordance signifiers (see Figure 9 and Appendix B.1 for illustrations) which were derived from an analysis of commercial habit-tracking apps and user interviews in the app design stage:

(1) The first feature enabled users to change the weekdays on which goal-pursuing activities were planned. Users could deliberately edit goals and alter their plans by adding, changing, or

deselecting weekdays. Autonomy affordance was signified by a calendar symbol, a heading reading “Days of the week”, and switches for each weekday.

(2) Users were able to add an activity to pursue one of their already created goals on every given day. This second feature means that users could spontaneously add a goal-pursuing activity to a day on which no such activity had been planned or to expand their plan for the day by an additional activity for the same goal. Autonomy affordance was signified by a plus button which was positioned next to the date of each day in the goal journal tab of the app.

(3) Lastly, users could also move an activity to another day. Thus, they were able to carry out activities earlier or later than initially planned. Moving an activity was enabled for all activities that had not yet been logged. Autonomy affordance was signified by a calendar button displayed next to each activity.

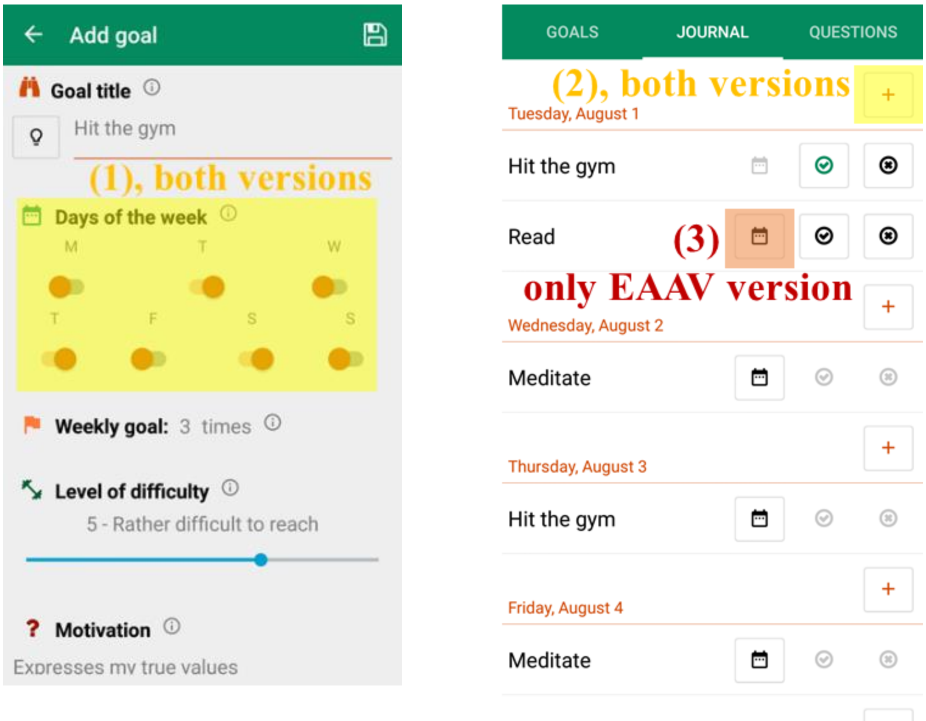


Figure 9: Screenshots of the App with the Three Autonomy Affordance Signifiers

In the low autonomy affordance version (LAAV), we included the first two features and autonomy affordance signifiers. It is important to note that users had the autonomy to decide on their plans regarding their goal-pursuing activities anyways. The question here merely was in how far and how easily the app allowed for changing the plan to fit the behavior. We included these first two features and signifiers for each user to provide enough autonomy within the app as not to frustrate users and not to impair the usage of the app. However, changing the weekdays (first feature) required users to edit goals and modify their overall weekly plan for the goals in a rather cumbersome fashion. Also, spontaneously adding activities for existing goals (feature (2)) required users to mark the activities that were substituted by the spontaneously added ones as not done and admit failure.

Autonomy affordance was only genuinely enhanced to a level above minimum usability requirements by the third presented feature and signifier. Smoothly moving activities within the journal alleviated the struggles mentioned above and enabled the users to modify their plans freely. The enhanced autonomy affordance version (EAAV) consequently comprised all three presented features and signifiers. By providing the features and signifiers (1) and (2) in both versions and all three in the enhanced autonomy version as shown in Figure 9, we aimed to achieve the difficult task of balancing user-friendliness (providing a minimum level of autonomy affordance so that users stay with the app) and differentiation between versions (providing considerably enhanced autonomy affordance as compared to the low autonomy affordance version).

Experiment Design and Procedures

We placed the app in the Google Play Store and the Apple App Store and advertised it via email and various social media channels as well as a local newspaper and a local TV channel. The experiment ran from April to September 2017.

The app uploaded all data to a cloud service - users were accurately informed about the intent and extent of data capture, upload, storage, and use and provided informed consent a priori. The data did not include any personally-identifying information. Starting with the first opening of the app, the upload was conducted every five days if a wireless network was available. If not, uploading via cellular data was delayed for three more attempts to spare data.

Either of the two app versions were randomly assigned after a user had installed the app. To sum up, we had two experimental treatments differing in the level of autonomy affordance (low autonomy affordance vs. enhanced autonomy affordance), random assignment of participants to treatments, and a between-subject comparison for the treatment variable enhanced autonomy affordance.

Measurement of Constructs

For the measurement of the constructs, we relied on log data that we acquired by tracking the goal-setting and goal-pursuing behavior of our field experiment's participants in the app. Creating, editing, and deleting goals, or logging, adding, and moving activities were logged. Based on this log data, the measures for the constructs could be calculated. Table 6 lists the nature of the collected log data and the definition of these measures.

Although an emoji scale to measure subjective well-being has not been validated yet, multiple similar scales (e.g., smiley scales) have been used to capture subjective well-being directly after experiences (Ross et al. 2015). Thus, we employ the feeling after logging indicated on a scale of five emoji as an unobtrusively and frequently surveyed measure of subjective well-being. Please see Figure 28 of Appendix B.1 for an illustration. Its log data provides a rather continuous and unobtrusive basis for analyses as compared to, e.g., a longer multi-item survey scale once a week.

Construct	**Operationalization based on log data**
Subjective well-being	An indication of the current emotional state after marking an activity as done or not done on a scale of 5 emoji (ranging from 1 representing frustration to 5 representing elation)
Goal performance	Number of goal-pursuing activities logged as done (rather than not done) divided by the sum of logged goal-pursuing activities; values from zero (for users who logged all activities as not done) to one (for users who logged all activities as done)
Enhancement of autonomy affordance	Binary indicator on whether the user was randomly assigned to the version of the app with low (0) or enhanced (1) autonomy affordance
Actualization of autonomy affordance	Sum of changes of weekdays on which goal-pursuing activities were planned for (first feature), spontaneously added activities (second feature), and moved goal-pursuing activities (third feature, available in the enhanced autonomy affordance app version) divided by the number of all activities in the observation period; values from zero (for users who did not actualize any autonomy affordance) to infinity (for users who often actualized autonomy affordance)
Motivation	Selection of the most suitable motivation for each goal from (English expressions adapted from Reis et al. (2000)): "Interesting or enjoyable" (intrinsic), "Expresses my true values" (identified), "Avoid anxiety or guilt" (introjected), or "Forced by external situation" (external)
Difficulty	Selection of the subjective difficulty of reaching each goal on a 7-point Likert scale with the anchors "1 - Very easy to reach" and "7 - Very difficult to reach"

Table 6: Measured Constructs, their Operationalization, and Calculations

Results

Descriptive Results

For our analyses, we consider the users who logged activities as done or not done for at least two weeks. We choose this minimum observation period to avoid biases caused by short-term, uncommitted users. This gives us a sample of n = 54. Considering the 49 users who answered the optional question about their age, the mean age is 29 years with a minimum of 17 years and a maximum of 60 years. Considering the 48 users who answered the optional question about their gender, the share of female users is 58 percent.

The separation of the examined participants into users of the LAAV (34 users, also see "Provision" in Table 7) and the EAAV (20 users) distinguishes users according to the autonomy affordance provided to them. However, whether the mere availability of affordance entailed its actualization remains to be tested. A comparison of the autonomy affordance actualization measure (see Table 6) of users who were assigned the EAAV with users who were assigned the LAAV yields an observable difference. Users of the EAAV exhibited a mean actualization of 0.083. In 74.9 percent of all times users of the EAAV actualized affordance, they used the third provided feature that was only available to them but not to the other group. Users of the LAAV showed a mean actualization of only 0.032. A Mann-Whitney-U test resulted in the rejection of the null-hypothesis that the two distributions of the actualization measure (20 EAAV users vs. 34 LAAV users) belong to the same population with a p-value of 0.012. This is a first indicator of the positive association of the provision of enhanced autonomy affordance and its actualization and provides support for H2. As both the provision of enhanced autonomy affordance (H1 and H2) and its actualization (H3 and H4) were hypothesized to influence the presented constructs, the following presentations of descriptive results will distinguish the users both regarding autonomy affordance provision and autonomy affordance actualization (see "Actualization" in Table 7).

The users entered between 1 and 19 goals with a median of 5 goals and 18 goal-pursuing activities per week. Typical goals include doing sports, eating more fruits or less sugar, studying a language, or getting up early. The median goal difficulty is 4 and the goals' median motivation is 2 (introjected). Users logged activities for periods up to 160 days, with a median of 34 days. A comparison using a Mantel-Haenszel test (Mantel and Haenszel 1959) which adapts the concept of survival curves for users of the two app versions suggests no significant group difference in the logging period (p-value of 0.249). Users logged between 4 and 100 percent of all activities, with a median of 95 percent. The observed goal performance is between 13 and 100 percent, with a median of 63 percent. I.e., across all users, 63 percent of planned activities logged by the users were done by them (according to self-report) while they failed to do 37 percent. The mean of the overall feeling after logging across all users is 3.51. Regarding activities logged as done, the feeling is 4.10. For activities logged as not done, the feeling after logging is 2.57.

Table 7 displays the results of the descriptive analyses separated into an enhanced (E) and a low (L) subgroup based on autonomy affordance provision (Provision; based on random assignment) or autonomy affordance actualization (Actualization; based on a median split according to observed behavior).

	Total (n = 54)	**Provision**		**Actualization**	
		E (n = 20)	**L** (n = 35)	**E** (n = 26)	**L** (n = 28)
Mean affordance actualization	0.05	0.08	0.03	0.10	0.01
Median number of goals	5	5	5	5	5
Median number of weekly activities	18	18	18.5	16.5	20
Median goal difficulty	4	4	4	4	4
Median goal motivation	2	2	2	2	2.5
Median logging period (d)	34	31	38	32	38
Median share of logged activities	0.95	0.98	0.93	0.98	0.87
Median goal performance	0.63	0.64	0.62	0.62	0.63
Mean feeling after logging	3.51	3.62	3.44	3.55	3.47

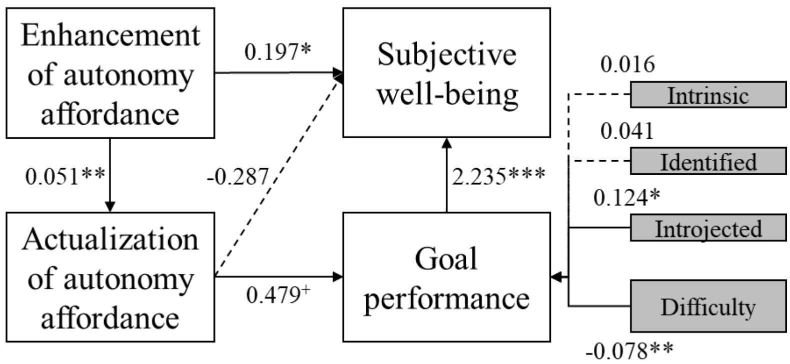
Table 7: Descriptive Results

Hypotheses Testing with Path Analysis

We hypothesized the enhanced provision of autonomy affordance to affect subjective well-being directly and positively (H1) as well as indirectly and positively via the mediator autonomy affordance actualization (H2 and H3). We expected autonomy affordance actualization to positively affect goal performance (H4), and goal performance to positively affect subjective well-being (H5). Additionally, we included the motivation and difficulty of goals as two important control variables.

We tested the hypothesized relationships by employing path analysis and utilizing the lavaan R package (Rosseel 2012). Path analysis allows for explaining relationships among directly measured, uni-dimensional constructs, both of which requirements are fulfilled given the operationalization of the examined constructs detailed in Table 6. Figure 10 depicts the results of the path analysis, including the estimated path coefficients and their significance level. H1, H2, H4, and H5 were supported while we found no support for H3.

Following Little and Kline (2016), we conducted a Chi-square test and calculated the fit indices RMSEA, CFI, and SRMR to assess our model. The Chi-square test statistic over the degrees of freedom results in an acceptable value of 0.804 (Gefen et al. 2000), whereas the p-value of 0.045 hints at suboptimal model fit (Barrett 2007). The RMSEA of our model is 0.130, with values smaller than 0.07 indicating good model fit (Steiger 2007). The CFI indicates a satisfactory model fit if higher than 0.90 (Hu and Bentler 1999) and amounts to 0.877 for our model. The SRMR should show values smaller than 0.08 (Hu and Bentler 1999) and is 0.077 for our model. Overall, we conclude that our model exhibits a moderate fit and include a discussion of this topic in the limitation. The R^2 values for subjective well-being, goal performance, and autonomy affordance actualization are 0.560, 0.277, and 0.108, respectively.



Notes: p-value significance codes *** for < .001, ** for .01, * for .05, + for < .1; unsupported relationships plotted in dotted lines

Figure 10: Results of Path Analysis including Path Coefficients

Discussion

We hypothesized the provision of enhanced autonomy affordance to directly and positively influence subjective well-being (H1), a relation that was found significant. This implies that the mere provision of enhanced autonomy affordance improved the users' feelings, even when controlling for the effects of actualized autonomy affordance and goal performance (users generally felt better after logging done than after logging not done). Hence, the provision of enhanced autonomy affordance lead to improved subjective well-being without it being actualized. It is important to note that this applies to the measurement of subjective well-being with a smiley scale as laid out in the methodology subsection and needs to be verified with other measures of subjective well-being in the future.

The provision of enhanced autonomy affordance was positively related to its actualization (H2). Users who were provided with an additional feature that allowed them to adapt the plans for their goal-directed behavior and who were presented with more autonomy affordance signifiers did indeed exercise the additionally provided options more often and actualized autonomy affordance to a greater extent.

The exercise of autonomy affordance, however, did not translate directly into higher degrees of subjective well-being as postulated in H3. This might indicate that the provision of enhanced autonomy affordance was sufficient to increase the users' subjective well-being. Its actualization might not be necessary to reap the benefits of a more autonomous feeling of the users on subjective well-being.

The actualization of autonomy affordance did, however, improve goal performance (H4). The actualization might have enabled users to react to unforeseen restrictions and bypass them, resulting in a higher goal performance due to the adaptability of their goal-pursuing behavior to their circumstances.

Lastly, subjective well-being was significantly and positively affected by goal performance (H5). The better the users of the app performed, the better they felt after logging activities as done or failed. This confirmation of H3 is intuitive and in line with a larger body of literature (Klug and Maier 2015; Koestner et al. 2002).

Therefore, we answer our research question as follows: The provision of enhanced autonomy affordance directly increases the user's subjective well-being. Also, goal performance is positively affected as enhanced autonomy affordance increases its actualization, which in turn increases goal performance. The positive effect of goal performance on subjective well-being, in turn, leads to an indirect effect of the provision of enhanced autonomy affordance on the users' subjective well-being. Interestingly, the mere provision of enhanced autonomy affordance seems to be sufficient to increase the user's subjective well-being, while the increase of goal performance requires affordance actualization.

The current work has three main implications that relate to our contribution to the underlying literature, the research instrument, and the design of self-tracking DTM. First of all, our hypotheses aggregate findings from various areas of IS research and psychology, such as well-being, motivation, and personality. Although only four of the five hypotheses are supported empirically, our results support the positive effects of the provision of enhanced autonomy affordance on its actualization, goal performance, and subjective well-being. Thus, our results strengthen the findings of Self-determination Theory regarding the relationship between autonomy and well-being presented in the theoretical background and hypotheses development subsections. More importantly, we demonstrate the underlying theory's applicability in the context of the design of DTM for self-tracking goal-directed behavior. To the best of our knowledge, this study is the first to argue and empirically demonstrate these effects in this context. Hence, our study contributes to the body of design knowledge in positive computing and self-tracking DTM. Besides, we have shown that the effect of autonomy might not originate from its actualization, but that its offering might already be sufficient. We add to Affordance Theory as we empirically observed that the mere provision of affordance can affect the users' subjective well-being while self-tracking goals.

Second, we created a measurement instrument by developing a mobile application that represents an easy way to capture the entirety of our model's constructs. Its design may facilitate similar research endeavors in the future. Once the app had been developed and distributed, it reliably and continuously captured empirical data and delivered it to our research team. The maintenance effort was limited to minor updates and the data analysis could be automated. Nevertheless, we recommend several refinements of the app's design before further applying it as a measurement instrument. Users should be able to enter goals that do not necessarily have at least one goal-pursuing activity a week. The app should allow goals with differing activity-rhythms as well. Next, users should be able to pass on goal-pursuing activities and not be restricted to either marking them as done or failed. This way, the app could implement pauses in the goal-directed behavior due to illness or vacation, track the users' activities more accurately, and afford the users with additional autonomy. The proposed refinements should improve the usability of the app, the amount of time for which users stay with the app, and the quality of the captured data.

Third, based on the results, we conclude that any self-tracking IS which is intended to further the success and well-being of its users while they work towards their goals should implement autonomy-supportive functions such as providing choices regarding goal-directed behavior.

Furthermore, we argue that the presented considerations on the influence of the provision of enhanced autonomy affordance on subjective well-being can be transferred to organizational contexts like universities, schools, and companies as well. In these settings, usually, both the goals and the DTM that is used to track the goal progress are predetermined by the organization. In contrast to self-tracking goals in the private, individual context where users freely choose the DTM and the goals themselves, the behavior of some organizational users might thus be significantly less autonomously regulated. This highlights the need for autonomy-supportive functions and stresses their potential to increase the well-being of the members of an organization. These effects are, in turn, likely to translate into benefits of monetary or reputational nature for the organization.

Conclusion

Limitations

The research process and results within Section 3.2 have limitations which highlight the need for further research about the interconnections of the provision of enhanced autonomy affordance, goal performance, and well-being in self-tracking DTM. First of all, although 54 individuals took part in the study for at least 14 days, the sample size is still quite small and the achieved empirical model fit is not optimal, which considerably impairs generalizability. However, we do not focus on the interpretation of the exact values of the coefficients. Still, we take significant results as the first confirmation of both the relationships between the dependent and the independent variables and its direction. Therefore, to verify our results, the study should be rerun after the refinements to the app that were proposed in the discussion subsection to achieve a larger sample size.

Second, the data that was collected by the app originates from self-reports by the users. Furthermore, according to interviews with several users who used the option to provide feedback, which was given during the experiment, their interpretations of not logging an activity differed. For some users, it had the equivalent meaning of logging an activity as not done. For others, it meant that they had simply forgotten to log and that the share of done and not done activities, if they had logged them, would have been similar to that of the days or weeks before.

Third, the installation and subsequent usage of a self-tracking app represent a form of self-selection. Not every individual knows about habit trackers, has access to them, or is sufficiently convinced of their usefulness to install and use them. Further research needs to develop an understanding of who the users of self-tracking IS are and why they track their behavior. It should be analyzed whether there are differences in personality, behavioral patterns, or other characteristics in comparison to non-users. Future studies should as well build on works like that of Gimpel et al. (2013) to determine which motivations lead users to engage in self-tracking. Similarly, it is yet unclear whether there are users who benefit more or less from the provision of autonomy affordance.

Summary

Research within this section examined the effects of the provision of enhanced autonomy affordance on its actualization, goal performance, and well-being in the context of self-tracking DTM for goal-directed behavior. Our theoretical development leverages Self-determination Theory and Affordance Theory and relates explicitly to the literature on self-tracking and positive computing. The theoretical hypotheses were mostly empirically supported in a field experiment. The empirical data was gathered via a mobile application that was developed for this purpose. The app collected self-tracking data about the goal-directed behavior of 54 participants who used it for a median observation period of 34 days. The results represent a first indication that self-tracking IS should afford autonomy to further both their users' goal performance and well-being.

Overall, our research and its further development contributes to positive computing and self-tracking IS and informs designers of self-tracking systems on the benefits of affording users with autonomy rather than telling them to defeat their weaker self and stick to their pre-determined plans regardless of the circumstances. Furthermore, it shows that in this context, merely affording more autonomy can have positive effects above and beyond the positive effects of the actualization of affordance.

With this, we hopefully supported users, despite exhausting working days, in reaching their goals and at the same time increase their well-being.

4. Analyzing the Effect of the Social Component

The digital workplace of employees consists of both technical and social components. Social components include humans (as individuals or social collectives) and their relationships, as well as attributes such as social capital, structures, cultures, and economic systems (Ryan et al. 2002). If one now considers the different levels at which, for example, methods to reduce employees' psychological risk can be applied, a social component in the work context can be understood as a combination of organization and person. Additionally, it also coincides with the differentiation of Williams and Schubert (2018) concerning the digital workplace. In this context, the organization is responsible for the workplace's design (tasks, processes, hierarchies) and the development of the corporate culture (Williams and Schubert 2018). This results in both job demands (e.g., workload, time pressure, role conflict) that affect employees and job resources (e.g., autonomy, feedback, social support) available to them (Demerouti et al. 2001). Nevertheless, since dealing with demands and the use of resources depends on the individual person, the employee's role must not be neglected. Therefore, personal dispositions that constitute additional demands (workaholism, perfectionism, emotional instability) (Bakker and Demerouti 2007), as well as additional resources (self-efficacy, optimism, work engagement) (Xanthopoulou et al. 2007), should be considered. Finally, it should also be taken into account that, in addition to the work domain, there is a private domain, whose boundaries are becoming increasingly permeable today, due to, for example, the digitalization of the workplace and the COVID-19 pandemic. These, accordingly, influence each other (Brummelhuis and Bakker 2012). Therefore, the research within this chapter focuses on organizational, private, and personal factors of the social component and their influence on employee health and productivity. Section 4.1 presents descriptive knowledge regarding the effect of the COVID-19 pandemic on employees' well-being, health, and productivity, taking into account different organizational, private, and personal factors. Subsequently, Section 4.1 presents descriptive knowledge regarding the effect of the individual coping style preference in dealing with upcoming technostress as a personal factor on employee exhaustion and productivity. Major parts of Chapter 4 conform with Regal et al. (2020) and Becker et al. (2020b).

4.1. Analyzing the Effect of Contextual Factors

In addition to the influences of a technical component's characteristics and features on instrumental and humanistic outcomes examined in the previous chapter, various organizational and individual factors of the social component are relevant. Thus, in this section, we will examine different characteristics of the social component that potentially amplify or mitigate the effect of the measures taken to combat the COVID-19 pandemic that radically disrupted work and private lives. While measures to reduce the spread of the SARS-CoV-2 virus mainly focused on increasing the physical distance between humans, digital technologies play a crucial role in keeping us socially close, connected, and collaborative. One of the key measures that many companies used to increase the physical distance among their employees themselves is telework that enables employees to be still productive. This is unprecedented in scale and speed of both pushing (e.g., for infection prevention) and pulling (e.g., for care obligations) employees in an alternate workplace, that is mostly at home (Bailey and Kurland 2002). According to Möhring et al. (2020), the maximum of people working from home reached 25% of all German workers during the COVID-19 pandemic with more than 50% in sectors like information and communication.

Consequently, work became more digital almost overnight regardless of workers' facilities and equipment for and experience with telework before the pandemic. Furthermore, this also increases the risk of employees being put under increased pressure, as teleworking is associated with the increased use of DTM (Tarafdar et al. 2013). This can potentially result in technostress, a form of stress that is caused by IT use for work (Tarafdar et al. 2007). Besides, due to social distancing measures and increased telework, the workplaces have not only changed to be more digital. Other changes relate, for example, to modifications in workload (e.g., to substitute for ill colleagues, childcaring colleagues, accommodate the changes for working in times of the pandemic), and increased private responsibilities (e.g., childcare due to closed schools and nurseries). All these disruptive changes lead to sudden shifts of workers' private and job demands as well as their private and job resources to cope with these demands. Hence, telework during the COVID-19 pandemic is an unparalleled duality of freeing workers from job design constraints in terms of time, location, routines, and autonomy while on the other hand leaving them alone with deficient technical, organizational, and social support.

To get a better understanding of the modified circumstances as well as their consequences on an individual psychological level, we aim to answer the following two RQ.

RQ1) How does the effort for physical distancing fostering telework affect demands and resources for the workforce?

RQ2) How do different contextual factors influence the effect of the COVID-19 pandemic on technostress?

To answer our research questions, we followed a quantitative-dominant mixed-methods research design (Venkatesh et al. 2013). First, we used two approaches in the qualitative phase to gain insights in the disruption caused by the COVID-19 pandemic: As an applicability check, we analysed journalistic articles from March and April 2020 (shortly after the start of the national German "lockdown" to prevent infections with SARS-CoV-2, which started in mid-March 2020 and lasted until late May 2020 when the lockdown was gradually relieved) in German high-quality national daily and weekly newspapers on changes at the workplace. Further, we conducted semi-structured interviews with expert practitioners as well as affected employees in different industries on fundamental changes at their workplace and the blurring of work and private life due to telework. Second, in the quantitative phase in May 2020 during the lockdown, we applied survey research to validate our derived hypotheses from the qualitative phase and re-sampled participants from a survey we conducted in March 2019. Both surveys focused on demands and resources (both job-related and private) with a focus on the digital workplace, IT use, and technostress from a large representative sample of German workers. Finally, in June and July 2020, we used a set of four specialist events to discuss the analytical results from the quantitative phase and to check the practical relevance of our findings.

The results of this rearch aim to contribute to the literature in two ways: empirical and practical. First, we provide empirical insights into digital work and its context in times of the COVID-19 pandemic based on qualitative and quantitative longitudinal data. Second, we provide insights into the severity of the COVID-19-related changes in job design for workers' well-being, health, and productivity as well as indications for measures to steer these effects if the situation persists or comparable disruptive situations should re-occur. Therefore, first of all, the theoretical background with regard to telework, which has not yet been presented in the dissertation, will be worked out. Afterwards a short introduction of the methodical procedure of the research within this section is given, before in the following subsection the hypotheses are derived as a result of the qualitative strand. The hypotheses are then tested in the course of the quantitative strand and their results are discussed in detail in the last subsection.

Theoretical Background

Telework has been defined "as working outside the conventional workplace and communicating with it by way of telecommunications or computer-based technology" (Bailey and Kurland 2002, p. 384; based on Nilles 1994). Prior research has long referred to it as being "mainly a good thing" (Gajendran and Harrison 2007). In their meta-analyses on telework, Harker Martin and MacDonnell (2012), as well as Gajendran and Harrison (2007), found that telework is associated with higher productivity, job satisfaction, performance, retention, organisational commitment, and lower role stress. As being one of only a few articles concerning the negative side of telework, Weinert et al. (2015) found that telework affects higher work overload, work-home conflict, and role ambiguity that, in turn, lead to telework exhaustion.

The last study can also be seen as a contribution to technostress research. Factors moderating the effect of technostress creators involve individual resources of the employees, such as technology self-efficacy, technology competence, control over access to task-related information, or personality traits (e.g., neuroticism, agreeableness, and extraversion) (Tarafdar et al. 2019). We use the JD-R as a meta-theoretical lens (Bakker and Demerouti 2007). The understanding in the JD-R research on demands and resources matches the understanding of technostress creators (demands) and moderators (resources). Therefore, the JD-R may well inform our research.

In times of the COVID-19 pandemic, the context in which demands and resources are experienced changed: Many employees were forced to work from home and to engage in telework. Thus, during their workday, individuals experience not only work demands that they are confronted with via digital technologies, but they also experience demands their private environment puts on them. Further, the availability of resources from the business environment may be less and has to be replaced by resources from the private environment in the home office. Since these rapidly changed conditions are new to technostress research, we lack insights on technostress creators and their interplay with environmental conditions and resources in a home office and telework context.

Research Process

To answer our two research questions, we apply a mixed-methods research design. Mixed-methods research designs "contain elements of both quantitative and qualitative approaches" (Tashakkori and Teddlie 1998b, p. 5). We have a multistrand design with a dominant quantitative strand (longitudinal survey data) and a qualitative strand with insights from articles in daily and weekly newspapers and interviews. Our purpose of mixing methods is developmental with the qualitative strand providing hypotheses to be tested by the dominant quantitative strand (Tashakkori and Teddlie 1998b; Venkatesh et al. 2013; Venkatesh et al. 2016). We adopted multiple paradigms as our epistemological stance. In the quantitative strand, we adopted post-positivism, in the qualitative strand interpretivism. We used a sequential sampling strategy with parallel samples and performed data analysis sequentially to help build the research model for the quantitative study from the results of the qualitative studies.

Overall, the mixed-methods design was divided into two strands and influenced by the guidelines for contextual research studies (Hong et al. 2014). The strands overlapped in time resulting in two phases of our research, as shown in Table 8.

Strand	Quantitative	Qualitative	Quantitative
Phase	—	1	2
Timing	March 2019	March and April 2020	May 2020
Aim	Establish a baseline for demands, resources, and technostress	Check applicability of theoretical perspective to work during COVID-19 induced social distancing	Analyse demands, resources, and technostress during COVID-19 induced social distancing
Data and analysis	Survey with 5,005 employees, data to be analysed in phase 2	Content analysis of articles in German daily and weekly newspapers and interviews with informants	Survey with 1,017 employees (subsample from the first quantitative strand), statistical analyses
Key inference	—	Relevance of technostress and JD-R theory; contextual insights for hypothesis development	Statistically and practically significant effects of COVID-19 induced social distancing on demands, resources, and technostress

Table 8: Overview of Strands and Phases of the Mixed-Methods Research Design

In the first phase, the qualitative strand, we accomplished the following: (1) content analysis of six recently published articles in top German daily and weekly newspapers to understand the effect of social distancing during the COVID-19 pandemic on employee's stress and technostress and to identify possible contextual factors that influence these relationships; (2) conduct five interviews with employees affected by social distancing and perform an applicability check (Rosemann and Vessey 2008) and conduct three interviews with experts on the fields of human resources, IT-support, and occupational health management to refine and enhance the previously elaborated understanding of the effect of the COVID-19 pandemic on employee's work in general and technostress in particular; (3) derive hypotheses based on (1) and (2). For more details on the data collection and analysis of the qualitative phase, please see Appendix C.1.

In the second phase, the quantitative strand, we (1) developed a questionnaire based on the identified effects of the COVID-19 pandemic and their relationship to technostress and distributed the questionnaire to participants of a previous study on technostress that was conducted prior the COVID-19 pandemic to build a longitudinal dataset (here, we only analyse data for the respondents who answered both surveys); (2) used different data analytics techniques to answer our hypotheses developed during the qualitative phase to identify statistical and practical significance (Mohajeri et al. 2020) differences between the responses to the two waves of the survey; (3) conducted multiple statistical tests for mixed designs to test further hypotheses to identify contextual factors that could influence the relationship between the effect of the COVID-19 pandemic and technostress. For more details on the data collection and analysis of the quantitative phase, please see Appendix C.2.

In Appendix C.3 and Appendix C.4, we further elaborate on our choices and research questions that guided the mixed-methods design and articulate how we followed established criteria for mixed-methods designs.

Hypotheses Development

In this subsection, based on the analysis of the data from the journalistic articles and the conducted interviews, we hypothesise about the effect of the COVID-19 pandemic and the associated increased conduction of telework on different demands and resources in the job and private life and the different contextual factors on relationships between social distancing and technostress. We provide direct quotes from the interviews to present our hypotheses in an understandable way. For more details on the data collection and analysis of the qualitative phase that is used for the hypotheses development, please see Appendix C.1.

The COVID-19 pandemic and the resulting lockdown had severe consequences for the working situation of employees. On the one hand, interviewees report that *"workload has [...] become less"* (Emp2) and that there are *"industries in which the orders have broken away"* (Exp1). This leads to companies having to close down, employees being sent on short-time work (even up to 100%), or having employees performing fewer tasks. However, this does not only concern large-scale changes in the amount of work. For example, one interviewee (Emp1) reports that the *"amount of work has decreased minimally because some small things have been omitted for example business trips and personal meetings have been eliminated"*. On the other hand, collaboration changes because *"informal communication between colleagues and managers is omitted, as you no longer see yourself on the spot"* (Emp1). Due to social distancing, conversations are increasingly performed using digital means of communication. However, this makes spontaneous and informal communication with the manager and colleagues more difficult. For example, one interviewee (Emp2) reports that *"the majority of [personal] meetings no longer takes place"*. Hence, it is *"a challenge for everyone how we keep each other up to date"* (Emp1) and one interviewee (Emp3) goes even further and notes that *"the lack of contact to colleagues is an increasingly negative element"*. At the same time, the IT department is being challenged by the rapidly growing demand for digital communication tools, by the dynamic introduction of new digital technologies, and by the increasing number of IT support requests that have to be resolved remotely. So, one interviewee (Emp3) reports: *"although we were already well prepared [for telework], there were performance problems in the beginning, e.g., with video conferences, because the usage increased so much"*. Further, the expert on IT (Exp2) reports that *"there are also some problems that cannot simply be solved remotely but require physical presence"*. Thus, we pose our first two hypotheses:

H1a: Job demands during the lockdown are less than before.

H1b: Job resources during the lockdown are less than before.

However, the increasing intensity of telework not only has an impact on the job but also on private life. As a result of increased telework, the boundaries between work and private life increasingly blur. This is supported by one of our experts (Exp1) who states, *"employees report that it is difficult to draw the line"*. This blurring, together with the increased presence of all household members at home, offers the potential that *"conflicts in the family increase"* (Exp1). Besides, the increased use of premises and equipment at home also leads to more household activities. In particular, people with a duty of care for children or elderly people report on lucidly increased private demands. One of our experts (Exp1) states that *"before [the lockdown] you could at least talk to [...] friends and acquaintances"*. At the same time, working from home offers employees who live with other persons in the same household the possibility of flexible support in case of problems and challenges. So, an employee (Emp5) reports that *"without my partner who is also conducting telework, the COVID-19 pandemic would be much more difficult to handle"*. Thus, we pose our next hypotheses:

H2a: Private demands during the lockdown are more than before.

H2b: Private resources during the lockdown are more than before.

In general, however, the journalistic articles and all the interviews show that the lockdown and the associated increase in telework substantially increased the use of digital technologies and media. An interviewee reported that (Emp4) *"now, much more digital communication is being used"*. Also, *"many companies were not technically prepared for a large-scale teleworking (e.g., missing laptops)"* (Exp1). Furthermore, an interviewee (Emp3) reports that *"there are often enough technical problems that cannot be solved ad-hoc"* and at the same time, the variety of digital technologies used in the workplace has also increased to meet the new business demands. Especially *"in the beginning it was a lot of new stuff, particularly for colleagues who are not so technologically advanced"* (Emp4) and some companies even have *"several tools for the same purpose"* (Exp2). Thus, we hypothesize:

H3: Technostress creators are more prominent during the lockdown than before.

Finally, when considering the changes brought about by the lockdown, the question arises as to how this ultimately affects productivity. Interviewee Emp2 reports that *"I have to get information from colleagues as needed to be able to do my job, because the other personal exchange is missing"* and interviewee Emp4 reports that especially *"in the beginning we were thrown in at the deep end and we were busy building everything up"*. This is in line with Schweitzer and Duxbury (2010) that as the level of virtuality increases, the quality of interaction in the team decreases. This leads us to our next hypothesis:

H4: Work productivity during the lockdown is lower than before.

After having hypothesized about the effect of the increased intensity of telework on demands and resources from job and private life, we now, based on the journalistic articles and the interviews, develop hypotheses about the contextual factors influencing the relationship between COVID-19 induced telework and technostress.

The respondents in the interviews reported on the challenges posed by increased teleworking. Often, this was justified by the fact to which extent already in the time before the COVID-19 pandemic a particular part of the working time was done from home. For example, *"how someone is equipped to work at home or what the family situation is like"* (Emp1). Employees who have already been teleworking should already have a functioning IT infrastructure to be able to carry out their work *"as from the office"* (Emp1). However, it was particularly challenging for employees who previously had little to no telework experience. Before *"video conferencing was very restrictive [before the lockdown], [...] regulations had to be relaxed and I have to use my own IT equipment at home, otherwise, I cannot work"* (Emp2). Furthermore, *"there was a lack of preparation for the employees, e.g., having a suitable workplace and someone looking after the children"* (Exp1). Besides, those employees already have experience both in dealing with the blurring of the boundaries between work and private life and in using digital technologies to collaborate virtually with colleagues and managers. This applies, for example, for employees who *"are already well prepared for working at two locations"* (Exp2).

> *H5: Employees who already spent a part of their working time via teleworking before the lockdown experience less change in the technostress level than employees who have no experience with teleworking.*

It is already known in the literature that managers are particularly affected due to their double role, *"managers are also employees or affected and have a double role which comes out very strongly [during the lockdown]"* (Exp1). This particular burden is also visible in the situation caused by the COVID-19 pandemic. *"For employees as well as for managers, the stress profile has changed a lot"* (Exp1). From an employees' point of view, it is crucial that managers remain accessible even in times of social distancing, provide feedback on their employees' work results, and offer help in case of problems. *"Informal communication is important because it strengthens the team coherence, exchange of information that ensures more innovation, and increases the bond with the company"* (Exp1). Interviewee Emp3 further explains that" *especially in my case as I lead employees, it is important to know how my people are feeling"*. At the same time, managers also act as role models in the use of digital technologies and media. This, therefore, requires them to be particularly reflective in times of intensive use of digital communication media. Otherwise, *"the moods of the other employees can be estimated less well"* (Emp3).

> *H6: Employees who hold a management position in the company experience more changes in technostress levels from lockdown-induced telework than employees who do not hold a management position.*

In addition to the organizational context factors already mentioned, personal characteristics can also be relevant. For example, it is already known from the literature of the job-demand-resource model that self-efficacy can act as a form of personal resource and therefore help to cope with different demands (Xanthopoulou et al. 2007). There was also evidence in the journalistic articles and the interviews so that employees who are more confident about teleworking are more likely to report less intensively about the challenges of the COVID-19 pandemic. Questioned about this, an interviewee reported that *"it is simply a matter of practice to get along with the technology"* (Emp3) and how important a certain basic attitude can also be as *"self-selection for conducting telework has been dropped and many employees are now permanently in the home office"* (Exp1). In this context, *"maintaining routines and having a structure and self-discipline"* (Emp1) and the possibility *"to control worries and fears [...] and to be able to seek help"* (Exp1) play an important role.

> *H7: Employees who think they can successfully perform telework experience less changes in the technostress level from lockdown-induced telework than employees who think they are less competent.*

Finally, we will discuss a factor that was discussed very prominently in society. Due to the closure of schools and childcare facilities and the lack of access to third parties, workers with children are particularly affected by the effects of the COVID-19 pandemic. One reason could be that some employees *"don't have anybody at home to distract me and so I get along quite well"* (Emp1). Employees conducting telework, for example, not only have to deal with their jobs but are also responsible for childcare, e.g., homeschooling. For example, there are challenges such as *"how do I communicate that I take a longer break at lunchtime to look after the children"* (Exp1) or *"I have to look after my child at the moment and am therefore not as efficient at some times"* (Exp1). Another interviewee (Emp5), one person with a child, reports how *"it is unpleasant to participate in telephone and video conferences when the child can be seen or heard in the background"*. Interestingly, the person concerned continues (Emp5) that *"on the one hand, this is because I disturb the other participants, but also because I do not want my private life to be visible to my colleagues and managers"*. The expert on HR (Exp3) also reports on *"challenges, especially for families where both parents work for us and how difficult it is to coordinate both partners and colleagues"*.

H8: Employees responsible for children or elderly people in need of care experience more changes in the technostress level from lockdown-induced telework than employees who do not have this responsibility.

After having developed the hypotheses from the qualitative part of our mixed-methods research process, the quantitative empirical analysis and validation of the hypotheses are carried out in the dominant quantitative phase.

Results

Changes in Demands and Resources

In order to answer our first research question on how the effort for physical distancing fostering telework affect demands and resources for the workforce, we analysed the gathered survey data by applying statistical tests to compare the reported values of demands and resources before and during the lockdown. Table 9 summarizes the results.

Physical distancing requiring telework affected both employees' demands and resources. Job demands such as workload, emotional requirements, and social conflicts decreased with a medium effect size. This supports H1a. Concerning H1b, we find that feedback from managers and colleagues became less, thus supporting our hypotheses of reduced job resources. However, the sense of community increased compared to the level before the lockdown. Thus, we can only partly support H1b. For private demands, we find that the considered private demands (i.e., emotional, mental, and quantitative demands as well as financial worries) are largely higher than before the lockdown. This supports H2a. Again, we find only partial support for resources: While social support rose during the lockdown as expected in H2b, family support decreased. Concerning technostress creators, we find ambivalent results. We find a decrease in techno-insecurity and techno-uncertainty and a slight decrease in techno-overload. For the other technostress creators, our results do not show significant changes at a 5% significance level. Thus, the data partially support H3. Lastly, as hypothesized in H4, we find the perception of decreased productivity during the lockdown.

Category	Construct	Before	During	Δ	p-value	Effect Size
Job Demands (H1a)	Workload	2.255	1.940	- 0.315	< 0.001	0.345
	Emotional Requirements	2.073	1.832	- 0.241	< 0.001	0.224
	Social Conflicts	0.913	0.779	- 0.134	< 0.001	0.221
Job Resources (H1b)	Feedback from Manager or Colleagues	1.849	1.804	- 0.045	< 0.001	0.108
	Sense of Community	2.906	2.966	+ 0.060	< 0.001	0.154
Private Demands (H2a)	Emotional Demand	1.350	1.407	+ 0.057	< 0.001	0.180
	Mental Demands	2.017	2.081	+ 0.064	< 0.001	0.200
	Quantitative Demands	1.691	1.767	+ 0.076	< 0.001	0.197
	Financial Worries	1.021	1.135	+ 0.114	< 0.001	0.253
Private Resources (H2b)	Family Support	2.857	2.786	- 0.071	< 0.001	0.251
	Social Support	2.594	2.634	+ 0.039	< 0.001	0.135
Technostress (H3)	Techno-Insecurity	1.054	0.937	- 0.117	< 0.001	0.131
	Techno-Complexity	1.065	1.085	+ 0.019	0.487	0.022
	Techno-Invasion	0.973	1.055	+ 0.083	0.005	0.089
	Techno-Overload	1.476	1.411	- 0.066	0.048	0.062
	Techno-Uncertainty	1.735	1.474	- 0.260	< 0.001	0.256
Job Outcome (H4)	Productivity	2.614	2.516	- 0.097	< 0.001	0.122

Notes: The columns "before" and "during" refer to lockdown and the average value for this variable during a period across all participants; scale for all variables ranges from 0 to 4; p-values calculated from paired Wilcoxon signed-rank tests; Wilcoxon R as effect size measure with 0.2 considered small, 0.5 medium, and 0.8 large (Tomczak and Tomczak 2014); n = 1,017

Table 9: Comparison of Demands and Resources Before and During the Lockdown

In summary, we see the increased use of teleworking to contain the COVID-19 pandemic had an impact on employees' demands and resources. While work demands decreased, during the lockdown, employees experienced higher levels of personal demands than before the lockdown. At the same time, job and personal resources hardly changed for the respondents. Concerning technostress, no clear statement can be made. While some technostress creators are perceived as less intensively, others are more present than before. Still, others have not changed significantly.

The Influence of Contextual Factors

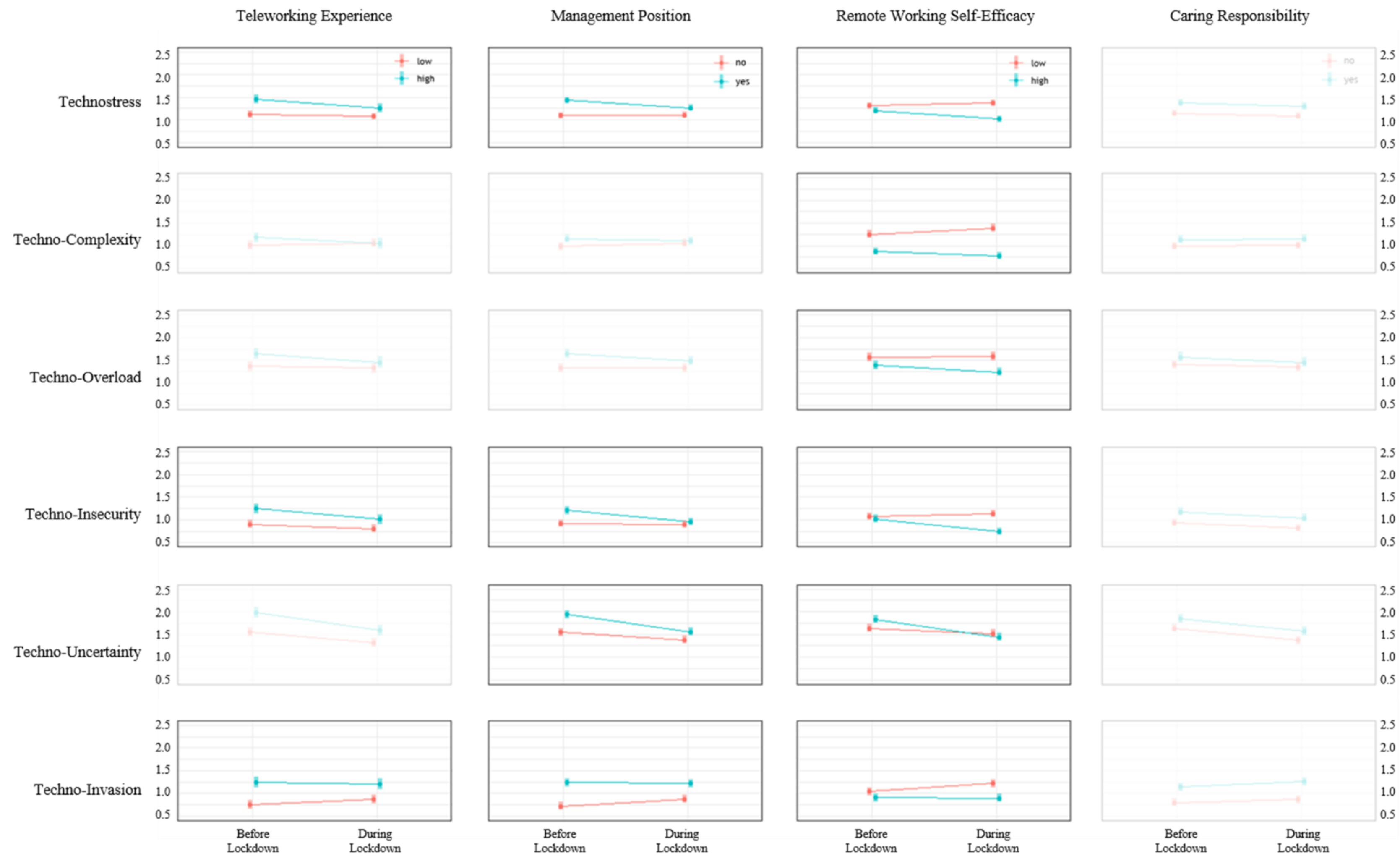
We now shift the focus to the second research question by examining the effect of different contextual factors on the intensity of technostress. The graphical presentation of the interactions are summarised in Figure 11 and the key data is placed in Appendix C.5.

Regarding the prior telework experience, a significant influence on the change of technostress compared to before the lockdown can be observed. People who already partially conducted telework before the lockdown then reported a higher intensity of technostress than employees with no or little telework experience. This difference diminishes during the lockdown so that the intensity of technostress for employees with telework experience is lower than before. At the same time, it remains almost unchanged for employees who did little or no teleworking before the lockdown. Thus, the two groups are converging. This observation also applies to the technostress creators techno-invasion and techno-insecurity. However, this does not support hypothesis 5, because, although the experience with teleworking influences technostress, employees with more experience report a lower intensity during the lockdown. In contrast, the intensity for employees with little experience hardly changes. Hence, employees with more experience are more affected by the increased intensity of telework than employees with no or less experience. Experience with telework is beneficial.

Regarding the fulfillment of a management position, a significant influence on the change of technostress compared to before the lockdown is likewise observable. Concerning technostress employees who hold a management position report a higher intensity of these facets before the lockdown than employees without a management position. This differentiation diminishes during the lockdown so that the intensity of the technostress decreases for managers. In contrast, for employees who do not hold a management position, the intensity hardly changes. This observation also applies to the technostress creators techno-uncertainty and techno-insecurity. However, the situation is different for techno-invasion. Here, hardly any changes can be detected for employees with a management position and that the intensity for employees without a management position increases. In sum, however, the two groups converge in terms of overall technostress and the technostress creators techno-invasion, techno-insecurity, and techno-uncertainty. This supports hypothesis 6 since, in most cases, the intensity for managers change. In contrast, the intensity for employees without a management position remained mostly unchanged during the lockdown compared to before.

Regarding self-efficacy in terms of telework, again, a significant influence on the change of technostress compared to before the lockdown can be observed. Compared to the other contextual factors, this applies to the intensity of overall technostress as well as to the intensity of all technostress creators. People with high self-efficacy regarding telework report a lower intensity before the lockdown than others and this differentiation even increases during the lockdown. However, the situation is different for the technostress creator techno-uncertainty. Here it can be observed that employees with high self-efficacy initially report a higher intensity than employees with low self-efficacy. However, this changes during the lockdown since the intensity for employees with a high self-efficacy is also reduced here. In contrast, the intensity remains almost constant for employees with low self-efficacy. Thus, the groups converge in terms of techno-uncertainty, while the differentiation in terms of the other technostress creators and overall technostress becomes greater. However, this does not support hypothesis 7, because although employees with higher self-efficacy report a lower intensity during the lockdown, the intensity for other employees hardly changes.

Regarding the responsibility for the care of minors or older people, there is no evidence that caring responsibility moderated the change of overall technostress or any of the technostress creators resulting from the lockdown. Thus, hypothesis 8 must be rejected.



Notes: Each image shows the effect of a contextual variable on the change in technostress and technostress creators. The estimated marginal means for the respective characteristics of the contextual factors at the two points before and during the lockdown are shown. Greyed out interaction plots are not significant according to the generalized van der Waerden test. Please see Appendix C.5 for more detailed information.

Figure 11: The Effect of Contextual Factors on the Change in Technostress and Technostress Creators Across Time

Discussion and Conclusion

Besides the quantitative analysis and our interpretation of the gathered data, we discussed our results during a set of four specialist events and checked for the practical relevance of our findings. The first one took place in the context of a presentation in front of more than 90 health and safety specialists. The second one was a network meeting between 30 CIOs of local companies who meet regularly to exchange information on various topics. The third event was a working group meeting of 15 works councils from different local companies. The fourth and final discussion with ten scholars on the topic of healthy use of digital technologies and media, in which psychologists, business IT specialists, computer scientists, and occupational physicians took part. In each event, we presented and discussed the research background, the analysis procedure, and the results focusing on the empirical contribution (in the sense of Ågerfalk (2014)) and practical relevance (in the sense of Mohajeri et al. (2020)). The results of all four events influenced the here reported discussion.

First of all and concerning RQ1, we found that teleworking indeed affected employees' jobs as well as private demands and resources. For demands, we found decreased job demands, whereas private demands increased due to the changing physical environment during the workday. The technostress creators show a more diverse picture. Whereas techno-invasion increased, techno-insecurity, techno-overload, and techno-uncertainty decreased other than expected. Techno-complexity did not show a significant change. Resources also did not show consistent results as some job and private resources decreased and some of them increased.

Second, and concerning RQ2, we found that prior telework experience as a form of resource enables employees to better deal with demands by the increasing usage of digital technologies and media associated with the lockdown. In general, however, we also observed that especially the employees with high teleworking-experience perceive a higher intensity of different technostress creators. This was especially true in the time before the lockdown and also in the time during the lockdown, even though the two groups of high versus low teleworking-experience got closer. This observation was also supported in discussions with CIOs and work councils during the specialist events. For example, one of the CIOs reported that before the lockdown, there was a four-page long regulation for telework. During the lockdown, these regulations were reduced to just one page. Thus, the special requirements for employees conducting telework became less demanding during the lockdown. On the other hand, one of the work councils reported that their employees would like to return to their regular desk after the lockdown to reduce the additional demand when performing telework (e.g., missing devices, missing services, lack of working space/room, unergonomic workplace).

Beyond that, employees in a management position also report a higher intensity of technostress creators before and during the lockdown than employees without a management position. It has been observed that employees with a management position do not notice any change in the intensity regarding techno-invasion. Employees without a management position, on the other hand, experience notably more techno-invasion during the lockdown than before. This could be scrutinised more precisely in discussions with some of the CIOs. For example, even before the lockdown, managers had to meet high demands regarding techno-invasion. The reasons for this are the higher demands on accessibility and the diversity of the different tasks. Hence, during the lockdown, the managers were already used to an increased techno-invasion. Thus, from their point of view, the intensity has hardly changed. Interestingly, however, CIOs have also spoken of generally higher demand on managers during the lockdown. The main reason for this is the rapid introduction and usage of new digital technologies and media to empower employees for telework. For employees holding a management position, this is creating new demands both on change management and on the applicable management style. However, these are not demands that are reflected in technostress creators, and therefore, a change could not be empirically determined.

If we now take a closer look at the personal resources of employees, we see that self-efficacy has a particularly severe mitigating effect on technostress. What is exciting to mention here is that this is just an attitude that can be changed. Self-efficacy is not competence in the narrower sense, but trust in one's abilities. Yet, one might expect a positive association between one's actual abilities and one's trust in one's abilities. A high self-efficacy (i.e., trust in his or her ability) has significant influence with a high effect size in the sense that prior to COVID-19, employees with high teleworking self-efficacy had lower technostress (as compared to employees with low teleworking self-efficacy) and during the lockdown, their technostress decreased further. On the contrary, at the outset, employees with low teleworking self-efficacy perceived higher technostress and this further increased during the lockdown. This empirical result was taken up with a great interest in the three practice-oriented events with the health and safety specialist, the CIOs, and the work councils. Besides, the various research experts also emphasized this aspect as particularly relevant from a scientific point of view, as self-efficacy exists in different areas (e.g., general (Bong and Skaalvik 2003), computers in general (Compeau and

Higgins 1995), virtual team competence (Fuller et al. 2006)) and can, therefore, be examined more closely in different research contexts.

Finally, we take a look at employees with caring responsibilities. We could observe that employees with a caring responsibility perceive a higher intensity of technostress and its creators before and during the lockdown. Nevertheless, the quantitative empirical results here were quite surprising for us because there is no significant influence on overall technostress before and during the lockdown - not even on a single technostress creator. This was unexpected as it was frequently mentioned in the newspaper articles as well as in discussions with health and safety specialists and work counsels that employees with caring responsibilities are particularly affected by the lockdown. In further discussions, it became clear that this does not apply to technostress, but rather to general work stress factors (i.e., workload, emotional demands, social conflicts). These are significantly higher for employees with a caring responsibility than for employees without. Thus, although changes can be observed for employees with caring responsibility, these do not relate to technostress.

The purpose of our mixed-methods research design was developmental: identify relevant factors and hypotheses from the qualitative strand and test the in the dominant quantitative strand. Accordingly, the main inference from the qualitative part was the set of changes in response to COVID-19 that affected individual demands and resources. The main inference from the quantitative part was that some of the hypotheses found broad empirical support.

The inferences of both strands, the qualitative and quantitative, were quite convergent, which shows a good quality of our results (Venkatesh et al., 2013). We also deduced divergent results, such as the not-existing effect of caring responsibility on the change in overall technostress and its individual technostress creators as expected from the qualitative strand. Many of the hypotheses developed in the qualitative study were empirically validated as significant and relevant in the quantitative study, although not all hypotheses could be validated. Although many results were statistically significant and relevant, some cause-effect relationships turned out to be contradictory. For example, it was expected that the characteristics of a contextual variable would influence the change in the overall technostress and its individual technostress creators. However, we could observe that in such cases, the characteristic does not influence the change but keep the intensity of overall technostress and its individual technostress creators on the same level as before the lockdown. In contrast, other characteristics of the contextual factor have then enabled that the intensity has become stronger or weaker compared to the time before the lockdown. In cases where the inferences reveal complementary or even divergent results, we further consult the literature to foster the credibility of our meta-inferences. Furthermore, it has also been shown that despite the major changes in demands and resources due to enforced telework, not all technostress creators have changed significantly or at least not to a relevant extent.

Empirical Contribution

Due to the quantitative dominant mixed-methods approach, our research provides empirical contributions to promote scientific discourse and derive practice-relevant implications. In doing so, we follow 's (2014) call for more empirical contributions. "An empirical contribution can then be thought of as a novel account of an empirical phenomenon that challenges existing assumptions about the world or reveals something previously undocumented "(Ågerfalk 2014, p. 594). Our empirical contributions are mixed qualitative and quantitative insights into telework, demands, resources, technostress, and its context in times of the COVID-19 pandemic.

In investigating the changes brought about by the lockdown and the resulting increased use of telework, we found that only a few technostress creators changed significantly. This is particularly surprising, since both the analyses of the newspaper articles, the empirical results and the discussions at the specialist events identified a substantial increase in the use and dissemination of digital technologies and media. At the same time, however, other stress factors such as the load of work, emotional demands, or social conflicts at the workplace are substantially lower than before the lockdown. This lets us conclude that technostress as a stress factor is not independent of other stress factors or that it is linked to other demands. For example, it is quite logical that techno-overload and techno-invasion increase with an increase in workload. Therefore, further research should explore the relationship between techno-stressors and other/traditional demands. Further, as the five technostress creators behaved differently, future research should keep on investigating them separately from each other rather than modelling the construct technostress as a second-order construct (e.g. Maier et al. 2019; Pirkkalainen et al. 2019; Ragu-Nathan et al. 2008; Tarafdar et al. 2007; Tarafdar et al. 2015). This more specific analysis of single technostress creators in a specific context meets Benlian's (2020) suggestions.

At the same time, although all job demands (both traditional and technostress creators) have decreased and the level of available resources has remained more or less constant, we have also seen lower self-assessed productivity. However, this cannot be explained by the JD-R model in its original form. Given that the increase in teleworking has blurred the boundaries between work and private life and increased private demands, lower job productivity is more understandable from a logical point of view. This supports the already existing new considerations regarding the JD-R and the integration of the influence of demands and resources from other domains (e.g., private, personal). For example, in one of the latest reviews of the JD-R, there is a call for research on the influence of private components on job performance (Demerouti and Bakker 2011) and other models such as the Work-Home-Resources Model are already trying to explain this in more detail (Brummelhuis and Bakker 2012). Therefore, further research should look more closely at the relationship between private demands or resource and job demands or resource, the two interwind processes (i.e., motivation and strain), and productivity.

Finally, we see the results of self-efficacy as another exciting empirical contribution. High intensity of self-efficacy in relation to telework has not only led to low levels of technostress and its creators before the lockdown. Moreover, it had even decreased the intensity during the extensive telework due to the lockdown. Self-efficacy is merely a conviction to cope well in teleworking situations. Whether employees with a high level of self-efficacy get along better with telework and whether this conviction is objectively understandable (e.g., based on training, existing skills, experience) seems on a first glance to be irrelevant for the impact on the overall technostress and the technostress creators. However, we would expect self-efficacy to correlate with actual skill and experience, and, thus, trust in one's capabilities could be a good approximation. To what extent the actual skill and experience are better suited as a facilitator should be considered in further analysis. Therefore, further research should more closely examine the relationship between self-efficacy, especially considering its myriad forms and technostress as suggested by Tarafdar et al. (2019) and additionally consider skill and experience. Furthermore, it would be interesting to analyse the difference between subjective beliefs about skills and objectively identifiable skills and how it affects technostress.

Practical Implications

While our research neither addresses Sars-CoV-2 nor COVID-19 directly, it delivers descriptive knowledge regarding the socio-economic implications and allows us to derive prescriptive knowledge on preventive and situational coping measures. This may lead to improved psychological health and productivity, which in turn may lead to prolonged individual and organizational acceptance of physical distancing measures. From a practical point of view, the severity of the COVID-19-related changes in job design for workers' well-being, health, and productivity was identified. Besides, the influence of different contextual factors on these changes was examined and thus provides insights into which employees are affected by lockdown induced telework. Concerning technostress, employees with less self-efficacy and few telework experience are more affected. Concerning private demands and resources, factors such as family members, caring responsibility matter. However, this does not result in an increase in overall technostress or one of its individual technostress creators. Surprisingly, managers were less affected by enforced telework than other employees. However, this only regards technostress and we do not have further insights on other responsibilities that come along with a management position (e.g., role model for employees, change management). Additionally, already Srivastava et al. (2015) pointed out that managers react differently on technostress by showing that technostress can also result in positive outcomes.

Based on the results of the empirical analyses and the discussions in the events, measures can be derived. For example, employees should be empowered to conduct telework parts of their working time. This creates the necessary conditions concerning the spatial equipment and availability of digital devices and services. In addition, employees gain experience with telework, which can lead to greater self-efficacy. Also, further training on working with digital technologies and telework can enhance the employees' trust in their ability. In summary, this may reduce the adverse effects of teleworking on technostress and show preventive indications for measures to steer these effects if the situation persists or comparable disruptive situations should re-occur.

Limitations

Our research is limited in multiple ways. Our hypothesis development is based on a small qualitative sample of six newspaper articles and eight interviews. Although we took care to select interviewees from a variety of job and personal backgrounds as well as experts from various disciplines, future research should aim for a broader sample, especially regarding managers. In addition, we explicitly focused our sample during the quantitative phase on those participants for whom there were no major changes (i.e., change of employer, job change, no reduced working hours, unemployment) compared to the time before the lockdown. Although this allowed us to investigate the influence of telework on technostress, future research should also explicitly examine employees and their job and private conditions, which were strongly affected by the COVID-19 pandemic, in order to take specific precautions for future scenarios.

Conclusion

COVID-19 radically disrupted our work and private lives. The move to teleworking is a key measure that many companies used to increase the physical distance among their employees themselves and to other people. However, our results show that increased teleworking to contain the COVID-19-pandemic impacted the work demands and resources of employees. Although the intensity of overall technostress decreased marginally compared to the time before the lockdown, this does not hold for all individual technostress creators. Besides, further discussions at specialist events with CIOs, health and safety specialists, works councils, and other scientific researchers have supported and complemented our findings.

From our point of view, employers should use the enforced conversion to telework and the resulting experiences to develop new technological, organizational, and personnel (i.e., both managers and employees) structures. In this way, the advantages resulting from the opportunity of conducting telework can be retained permanently and possible risks can be mitigated. At the same time, companies become more resilient and are less susceptible to similar situations in the future.

4.2. Analyzing the Effect of Individual Coping Style

In addition to the context factors examined in the previous section, however, it also plays a crucial role how employees deal with demands that have already occurred also plays a crucial role in how these affect instrumental and humanistic outcomes. As already discussed, it has been shown technology-related factors which induce stress are associated with a reduction in productivity, job satisfaction and loyalty to the employer as well as an increased risk of burnout and a poor work-life balance (Ayyagari et al. 2011; Califf et al. 2020; Khaoula et al. 2020; Srivastava et al. 2015; Tarafdar et al. 2010; Tarafdar et al. 2011). To overcome these issues, employees use different coping strategies depending on the situation, with the choice being influenced by personal preferences and the availability of job and personal resources. An examination of these coping styles is particularly relevant in that, while research has identified several organizational and individual factors that positively moderate the relationship between techno stressors and health as well as organizational outcomes (Srivastava et al. 2015; Tarafdar et al. 2015) most of them are outside the individual's scope of influence. They are either organizational factors (Ragu-Nathan et al. 2008) or inherent stable personality traits (Sumiyana and Sriwidharmanely 2020).

But little is known about actual behaviours or thoughts that the individual deploys to mitigate the harmful effects of technostress. There are a few studies concerned with coping, but these conceptualize coping as a mediator between technostress and strain in line with the transactional model of stress (Lazarus and Folkman 1984). In contrast, research from industrial and organizational psychology emphasizes the role that coping plays as a personal resource (Searle and Lee 2015) moderating the relationship between job demands and strain (Bakker and Demerouti 2017). Accordingly, the neglect of coping as a moderator proposed by Frese (1986) is still present within the research field of technostress in information systems (IS) and was only recently addressed by few research articles (Nisafani et al. 2020; Pirkkalainen et al. 2019) focusing on the role of proactive and reactive coping (Pirkkalainen et al. 2019). Hence, coping responses concerning technostress are under-studied and interdisciplinary theoretical enrichment between psychological literature and IS research is needed (Pirkkalainen et al. 2019; Tarafdar et al. 2019). The disciplines share a common and joint research interest but yet, most articles about technostress are published in IS journals and only few in psychological journals disrupting the flow of information, knowledge and exchange of theories from one discipline to the other (Bondanini et al. 2020).

In this section, we aim to provide evidence that coping as a personal resource moderates the relationship between (techno)stress and strain as proposed by the JD-R (Demerouti et al. 2001) extending the perspective to coping as a mediator of emotional responses that is grounded in the TMS (Lazarus and Folkman 1984). Thereby, we contribute to research by investigating the influence of technostress and coping on organizational and individual-level outcomes while modelling coping as a moderator in line with the workplace-specific JD-R. This includes the conceptualization of strain mediating the influence of technology related demands on work productivity. Furthermore, we emphasize the importance of distinguishing between functional and dysfunctional coping, two forms of reactive coping, to gather insights about the differentiation of effective and less effective ways to overcome strain related to the use of digital technologies.

The present section is structured as follows: first, we will address the theoretical background and give an overview of the current research streams in IS and psychology regarding the negative consequences of DTM use. Subsequently, based on the existing literature, we designed a conceptual model that integrates the relationships between techno stressors, their impact on strain, well-being, and organizational outcomes as well as the moderating effect of individual coping behaviours. This model guided our empirical study on the impacts of technostress.

Lastly, we will summarize and carefully discuss the empirical findings and give an outlook for future research.

Theoretical Background

Technostress

The concept of technostress is anchored in the TMS (Lazarus and Folkman 1984) in which stress is a process where individuals appraise the demands of a given situation as taxing or exceeding their resources while interacting with their environment. Consequently, technostress refers to stress which arises during the usage of DTM (Tarafdar et al. 2019). Tarafdar et al. (2007) emphasize that "in the organizational context, technostress is caused by individuals' attempts and struggles to deal with constantly evolving information and communication technologies and the changing physical, social, and cognitive requirements related to their use" (p. 304). Hence, employees might experience technostress due to an increased usage of DTM at the workplace (Ragu-Nathan et al. 2008).

To reduce technostress, Ragu-Nathan et al. (2008) investigated three situational factors and organizational mechanisms: technical support, literacy facilitation (users are encouraged to share their experiences with and knowledge about new technologies), and involvement facilitation (users are consulted in the implementation of new technologies and are actively encouraged to try them out). These technostress-inhibitors operated as moderators of the relationship between technostress and job-satisfaction, organizational commitment, and continuance commitment. Other factors that influence the relationship between techno stressors and outcomes are timing control and method control (Galluch et al. 2015). Furthermore, individual moderating variables like technology self-efficacy (Tarafdar et al. 2015) and personality traits like openness, agreeableness, neuroticism, and extraversion (Srivastava et al. 2015) have been identified.

Coping with Technostress

According to the TMS (Lazarus and Folkman 1984, p. 141), coping is defined "as constantly changing cognitive and behavioural efforts to manage specific external and/or internal demands that are appraised as taxing or exceeding the resources of the person". These efforts are commonly classified into different styles of coping. Besides the broadly acknowledged distinction between problem-focused coping (directed at the problem itself in terms of modifying or improving the person-environment relation) and emotion-focused coping (comprising strategies which aim at regulating stressful emotions) proposed by Folkman et al. (1986), more fine-grained taxonomies include active coping, seeking instrumental social support, religion, positive reinterpretation, mental disengagement or behavioural disengagement—only to name a few (Carver et al. 1989). In a more detailed approach, 14 different coping styles have been differentiated (Carver 1997). Thereby, active coping and seeking instrumental social support can be subsumed under problem-focused coping, whereas positive reinterpretation and turning to religion are examples of positively related emotion-focused coping. Hence, these two higher-level categories reflect active-functional strategies (Prinz et al. 2012). In contrast, coping strategies where individuals try to avoid the overall issue and escape from the problem instead of tackling it at source are considered as dysfunctional. Examples are mental and behavioural disengagement as well as alcohol and drug consumption (Carver et al. 1989).

Research using this more fine-grained taxonomy found that active coping is associated with lower exhaustion (Gaudioso et al. 2017). The use of active-functional strategies, such as seeking social support, is negatively associated with burnout (Erschens et al. 2018). It has also been observed that maladaptive, dysfunctional coping like behavioural disengagement is associated with increased work exhaustion (Gaudioso et al. 2017; Prinz et al. 2012) and strain (Hauk et al. 2019). In total, there is some evidence that active-functional coping strategies positively influence employees' well-being and organizational outcomes, whereas dysfunctional coping negatively impacts those outcomes. However, it is not clear how coping moderates the relationship between techno stressors and organizational as well as health outcomes. Active-functional coping should be beneficial, whereas dysfunctional coping may be seen as a malfunctioning strategy to overcome the long-term consequences of stress.

Currently, there is no consensus in research whether coping strategies should be considered as a moderator or mediator. Frese (1986) mentioned this issue in his study and highlights that this specific distinction is often neglected. As emphasized above, the technostress framework from IS literature is based on the work of Lazarus and colleagues (Folkman et al. 1986; Lazarus and Folkman 1984) where coping is seen as a mediator. This has already been addressed by several studies in the context of technostress research (Gaudioso et al. 2016; Hauk et al. 2019; Zhao et al. 2020). Maladaptive coping, for example, translates invasion and overload through the strain facets of work-family conflict and distress into higher exhaustion. In contrast, adaptive coping strategies mediate the same relationship resulting in lower work exhaustion (Gaudioso et al. 2017). Behavioural disengagement mediates the relationship between age and technology induced strain that was operationalized as emotional and physical exhaustion (Hauk et al. 2019).

At the same time, stressors and work demands which also include stress resulting from the use of DTM constitute a typical subject of matter in psychological investigations (Barber et al. 2019; Braukmann et al. 2018; Day et al. 2012; Day et al. 2020; Golden 2012; Sonnentag et al. 2010). In this context, coping strategies have been discovered numerous times as a moderating variable: Lewin and Sager (2009) found that problem-focused coping strategies moderate the impact of stressors on emotional exhaustion. Yip et al. (2008) provide evidence that coping buffers the negative effects of job stressors on burnout. Similarly, Searle and Lee (2015) found that pro-active coping moderates the relationship between demands and burnout. Ashill et al. (2015) show in their study that self-directed coping mitigates dysfunctional effects of job demand stressors on emotional exhaustion while other-directed coping buffers the relationship between job demands and job performance. Recently published articles in IS also started to model coping as a moderator (Nisafani et al. 2020; Pirkkalainen et al. 2019)

Investigating coping as a moderator, psychological research widely uses the JD-R model (Demerouti et al. 2001) as the theoretical foundation which has been applied and expanded to explain the relationship between job demands, personal resources and strain (e.g., exhaustion as one facet of burnout (Demerouti et al. 2010)). In keeping with the JD-R model, "job resources refer to those physical, psychological, social, or organizational aspects of the job that may do any of the following: be functional in achieving work goals, reduce job demands and the associated physiological and psychological costs, stimulate personal growth and development" (Demerouti et al. 2001, p. 501). ”Personal resources can be seen as the beliefs individuals have in their ability to act on the environment" (Bakker and Demerouti 2017, p. 275). How people cope with stress can be treated as a personal resource as well (Searle and Lee 2015). Personal resources can buffer the impact of job demands on strain while strain variables like exhaustion negatively affect employees' job performance (Bakker and Demerouti 2017). According to Ninaus et al. (2015) and Patel et al. (2012), it can also be differentiated between demands and resources within DTM use. Employees may benefit from DTM use, but it also increases demands and therefore causes strain (Bakker and Demerouti 2017). These resources also include coping strategies to directly mitigate strain (Ângelo and Chambel 2014). The JD-R model has also been used as a theoretical foundation for conceptualizing technostress (Christ-Brendemühl and Schaarschmidt 2020; Florkowski 2019; Mahapatra and Pati 2018b; Ninaus et al. 2015; Wang et al. 2017) but it has not been applied in investigating coping strategies as a moderator in the technostress context yet.

Hypotheses Development

We are referring to the agenda postulated by Tarafdar et al. (2019) who claim a lack of research on coping strategies and its effects on the relationships between techno stressors and outcomes. Simultaneously, other researchers (Nisafani et al. 2020; Pirkkalainen et al. 2019) call for further investigations of coping strategies and how they might lead to different coping outcomes. To fill this gap, the respective moderating effects of active-functional and dysfunctional coping behaviour are the focus of our examination. Another reason for this is that Pirkkalainen et al. (2019) focus on the effects of proactive (i.e., strengthening one's ability to cope) and reactive coping, neglecting the different types of reactive coping. Based on the findings above, we developed a research model (the simplified moderated mediation model is displayed in Figure 12) building on both psychological literature regarding job demands as well as negative consequences of DTM use and technostress literature from the IS domain.

The model establishes a relation between job demands, strain (represented through exhaustion), and job performance (represented through productivity) - with strain mediating the impact of job demands on job performance - as well as the moderating effect of coping as a resource which is in line with the JD-R model (Bakker and Demerouti 2017). Furthermore, the direct effect of coping on strain, as proposed by Ângelo and Chambel (2014), is included. To our understanding, the techno stressors described above represent technology-related job demands resulting from the use of DTM for work purposes. The wording 'demands' will be subsequently used. Therefore, in the model, the second-order construct job demands comprises the five techno stressors (Tarafdar et al. 2007) mentioned and explained above: complexity, insecurity, invasion, overload, and uncertainty. Also, interruptions and unreliability (DTM hassles) that were identified as affective events related to DTM use that may have negative consequences for well-being (Braukmann et al. 2018) were included.

In line with the proposed model, we deduct hypotheses for the relationships between job demands, exhaustion, productivity, and coping. It has been shown that technostress is associated with lower productivity and simultaneously, techno stressors can induce strain. Further, the JD-R model proposes that strain translates into lower job performance, so we assume:

H1a: Job demands are negatively associated with the productivity of employees.

H1b: The relationship between job demands and productivity is mediated by exhaustion

Even though the psychological framework of the JD-R model has already been applied in the technostress context (Day et al. 2020; Florkowski 2019; Mahapatra and Pati 2018b; Ninaus et al. 2015; Patel et al. 2012; Wang et al. 2017), there is no research concerning coping strategies moderating the relationship between techno stressors and outcomes yet. For investigating these effects in our model, we differentiate between active-functional and dysfunctional coping. First, active-functional coping (like support-seeking behaviour and searching for solutions or improvements in a stressful situation) is associated with a lower level of exhaustion. In contrast, dysfunctional coping (like displacing reality, escaping behaviour, and the consumption of alcohol or drugs) is related to an increased level of exhaustion, we propose accordingly:

H2a: Active-functional coping is negatively related to employees' level of exhaustion.

H2b: Active-functional coping acts as a moderator, mitigating the negative impact of techno stressors on exhaustion.

H3a: Dysfunctional coping is positively related to employees' level of exhaustion.

H3b: Dysfunctional coping acts as a moderator reinforcing the negative consequences of techno stressors on exhaustion

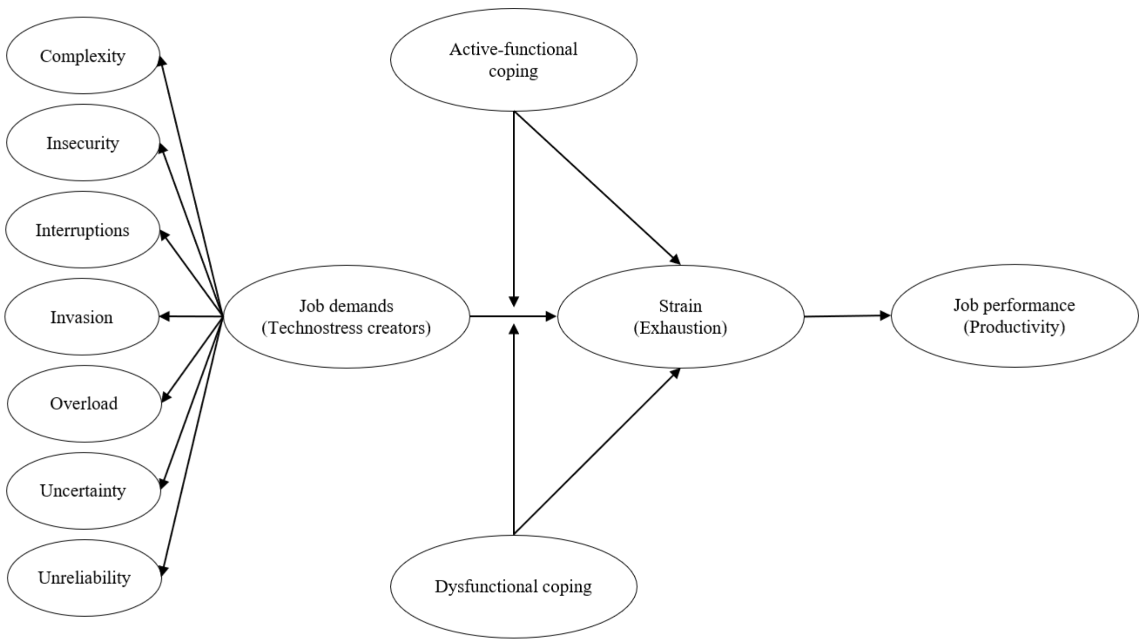


Figure 12: Research Model of the Assumed Relationships

Methodology

Sample

Data for this study was collected within the setting of a larger research project which is supervised by an interdisciplinary committee from which ethical approval for the survey was obtained. Respondents were acquired via an external research panel and paid a small incentive for participation in the study. Participants gave informed consent which means they actively agreed that they are over 18 years of age, have read the information on intentions of the research project, ethics and processing of data and data protection by ticking a box. A contact person was listed, and they were informed that they had the possibility to withdraw their consent to participate without giving reasons or incurring disadvantages at any time. Subjects were guaranteed that their answers were collected anonymously as far as possible. "Protecting respondent anonymity and reducing evaluation apprehension" helps to reduce possible common method bias (Podsakoff et al. 2003, p. 888). To do so, we reminded participants that there are no right or wrong answers and that we are interested in their honest opinion at the introduction of each subsection, trying to minimize method bias. The panellist company was instructed to collect answers from German knowledge workers. Knowledge workers are defined as employees working in an occupation where information is a resource, tool and result of work (Klotz 1997). Examples for relevant professions are technicians, engineers, scientists, finance, controlling, managers, journalists, consultants, and lawyers. The questionnaire included control variables to test for representativeness of our sample, namely age, sex, employment status, occupational title and sector, number of hours worked per week, and education. Further, intensity of technology use for work purposes was assessed. In the first step, the answers of n = 445 participants were collected for a quantitative pre-test of the scales. In a second step, answers for the main study were collected. This final sample consisted of n = 3,362 respondents. Preliminary analysis showed that the distribution of participants according to the control variables age, sex, and sectors (Federal Statistical Office of Germany 2018a, 2018b) is representative of the German working population. About 46% percent of participants were female and 54% male. The mean age was 42.44 years (SD = 11.39). 23% of the participants have a secondary school education, 27% finished a vocational apprenticeship, 19% had a bachelor's degree, 27% finished with a master's degree, and 4% percent completed a Ph.D. Most participants (30%) worked in the public or private service sector, followed by 15% who worked in the trade, transport or hotel sector, followed by the producing sector without construction industry (15%), business services industry (14%), information and communication (11%), finance- and insurance services (7%), construction sector (4%), land- and housing sector (2%), and agriculture, forestry and fishing (< 1%).

Measures

We relied on established, validated scales in the survey. All questions were administered in German. If necessary, the items were translated from the original language. Therefore, three German native speakers translated the questions in parallel. They met afterward to resolve discrepancies and agreed on the best translation. In this step, we tried to avoid common method bias. The following rules were applied to all items in the translation procedure: "keep questions simple, specific, and concise; avoid double-barrelled questions; decompose questions relating to more than one possibility into simpler, more focused questions; and avoid complicated syntax." (Podsakoff et al. 2003, p. 888). The measures were subjected to extensive testing with participants that had not been involved in the research process previously to identify ambiguous terms and to ensure understanding of the translated items. In this quantitative pre-test, the quality and psychometric properties of the scales were evaluated based on the answers of $n = 445$ participants.

Complexity, insecurity, invasion, overload, and uncertainty were assessed with the scales developed by Ragu-Nathan et al. (2008). Complexity was measured using five items, for example: *"I need a long time to understand and use new technologies"*. The scale for insecurity encompasses five items, including *"I have to constantly update my skills to avoid being replaced."* Invasion comprises three items (e.g., *"I have to be in touch with my work even during my vacation due to this technology"*). Overload was measured with four items. An example is *"I am forced by this technology to work with very tight time schedules"*. Lastly, uncertainty was measured with four items (e.g., *"There are constant changes in computer software in our organization"*). Additionally, interruptions were assessed with three items published by Galluch et al. (2015), for example, *"I experienced many distractions during the task"* and finally, unreliability (Ayyagari et al. 2011) was also measured with three items (e.g., *"The features provided by digital technologies are dependable"*). We used a five-point Likert-type rating scale from 0 = *I do not agree at all* to 4 = *I totally agree* for all items.

Exhaustion was measured with a subscale of the Maslach Burnout Inventory (Maslach and Jackson 1986). It contains nine items, for example, *"I feel emotionally drained by my work"*.

A five-point Likert-type rating scale ranging from 0 = *I do not agree at all* to 4 = *I totally agree* was used.

Productivity was measured with four items (Chen and Karahanna 2014). It describes self-evaluated work performance (fulfilment of work tasks and general demands). An example item is *"I have a reputation in this organization for doing my work very well"*. Ratings were made on a five-point Likert-type rating scale ranging from 0 = *I do not agree at all* to 4 = *I totally agree*.

Coping was assessed with a selection of 15 items from the Brief COPE (Carver 1997). We used the existing German translation of the inventory (Knoll et al. 2005). While the original scale contains 28 items paired up in 14 subscales with two items each, the subscales from Prinz et al. (2012) that build on the Brief COPE consist of nine items for active-functional coping and six items for dysfunctional coping. Active-functional coping comprises nine items, for example, *"I've been taking action to try to make the situation better"*. Dysfunctional coping includes six items. An example is *"I've been using alcohol or other drugs to make myself feel better"*. Answers were assessed on a three-point frequency scale ranging from 0 = *never* to 2 = *often*. The items are displayed in Table 43 in Appendix D.2.

The covariate technology use was assessed with one self-developed item: "*How often do you use digital technologies for your work?"*. Frequency answers were given from 0 = *never* to 4 = *several times a day*.

Means of Analysis

After running descriptive analyses, we subjected the items for the two coping subscales identified by Prinz et al. (2012) to an exploratory factor analysis (EFA) with varimax rotation (Appendix D.1) to see whether the expected two factors are extracted because the authors of the original scale did not provide this clustering (see Appendix D.1). The relationships of the variables which we propose in our research model were analysed by the mean of covariance-based structural equation modelling (Jöreskog 1970). We utilized the widely used open-source software R and the integrated development environment R-Studio (R Development Core Team 2019; RStudio Team 2019). For specific analyses, we used complementary packages in addition to the R base program (i.e., lavaan (Rosseel 2012), psych (Revelle 2019), GPARotation (Bernaards and Jennrich 2005), and semTools (Jorgensen et al. 2019)).

For the testing of nonlinear and interactive effects in structural equation models, Kenny and Judd (1984) proposed the product indicator (PI) approach. The products of the observed variables are used as indicators for the latent interaction term in the measurement model. To create the product term, the indicator with the highest reliability should be chosen (Saris et al. 2007), while the product shows optimal reliability as an indicator of the latent interaction variable, whereby the power of the test of the latent moderator increases by an increase in the reliability of the indicator (Saris et al. 2007). When using product indicators, missing independency of higher-order indicators from the lower-level indicators due to the multiplication of the two variables is a problem. Statistical procedures have been introduced to deal with this dependency of higher-order indicators to lower-order indicators. Lin et al. (2010a) propose a double mean centring strategy. This approach performs well and eliminates the need for the constraint of the inclusion of a mean structure, as introduced by Jöreskog and Yang (2013). Double mean centring also performs better with non-normal data than (single) mean centring and orthogonalization. It can be combined with different matching strategies of indicators and is available with most commercial SEM software. Hence, to create the indicators for the latent interaction term between techno stressors and coping, we used the PI approach in which indicators were chosen and matched according to reliability. The product terms were double mean centred (Lin et al. 2010a).

Results

Measurement Models

Preceding the analysis of the proposed relationships in our hypothesis, we tested the measurement models of the endogenous (strain and productivity) and exogenous (job demands and coping) latent variables. Job demands were modelled as a second-order construct (reflected in the seven technology-related stressors) with both first-order and second-order indicators being reflective. The moderated mediation was set up as described by Hayes (2013) and based on the in-depth explanations (Stride et al. 2019). Coping is moderating the relationship between the independent variable (IV) job demands and the mediator exhaustion (IV–Mediator path) and, further, has a direct effect on exhaustion as well.

We first assessed means and standard deviations, item reliabilities (loadings), and internal consistency (Cronbach’s alpha). Table 10 shows an overview of the scales’ properties. For brevity of presentation, the values in the table reflect the final measurement models, after deletion of single indicators.

Cronbach’s alpha was above 0.70 for all constructs, as recommended (Nunnally and Bernstein 1994). The test of item reliabilities showed good results. The factor loadings for each indicator should be above the value of 0.70 that indicates that the underlying latent factor accounts for more than 50% of the variance in the respective indicator (Fornell and Larcker 1981). Most loadings met this threshold. For the items of the two coping constructs and one item of invasion, values below the threshold of 0.70 were observed. The reliability of constructs is evaluated by the AVE. It determines whether the latent construct accounts for more than 50% of its indicator’s variance on average. This threshold was met by invasion and dysfunctional coping, whereas it was below 0.50 for active-functional coping due to very low loadings, even below 0.60. The two items with the lowest loading were removed, which improved the AVE of active-functional coping to 0.51. Further, two items of the latent interaction term between active functional coping and technostress displayed loadings below 0.60. Hence, they were taken out of the model as well.

Scale	**Items**	***M***	***SD***	**Loadings**	**α**
Complexity	5	1.22	1.04	0.77–0.87	0.91
Insecurity	5	1.23	1.03	0.72–0.82	0.87
Interruptions	3	1.59	1.16	0.85–0.90	0.90
Invasion	3	1.28	1.12	0.64–0.88	0.82
Overload	4	1.62	1.10	0.70–0.85	0.88
Uncertainty	4	1.80	1.04	0.74–0.85	0.87
Unreliability	3	1.82	1.10	0.85–0.92	0.91
Exhaustion	9	1.50	1.09	0.76–0.91	0.96
Productivity	4	2.62	0.85	0.81–0.83	0.89
Active-functional coping (A)	6	0.73	0.60	0.68–0.76	0.86
Dysfunctional coping (D)	4	0.28	0.45	0.62–0.79	0.80

Table 10: Descriptive Statistics, Factor Loadings, and Reliability of the Scales

Internal consistency measures like Cronbach’s alpha are not sufficient to imply homogeneity and unidimensionality of constructs (Tavakol and Dennick 2011). Hence, in addition, we analysed the discriminant validity of the latent endogenous constructs with the Fornell-Larcker criterion (Fornell and Larcker 1981) based on AVE and the correlations among the latent constructs. It is considered as given if the square root of the AVE (printed along the diagonal of the correlation matrix) is higher than the correlations with the other latent variables (off-diagonal elements) (Fornell and Larcker 1981). The results are displayed in Table 11. All correlations between the latent variables were significant at the level $p < 0.001$. The square root of the AVE printed along the diagonal is higher than the correlations with respective other components for each of the latent factors. This suggests that the discriminant validity of the endogenous constructs in our model is given.

In addition to the procedural remedies which we have taken to avoid common method bias, which is described in the method section, we conducted Harman‘s single factor test (Harman 1967) to infer whether common method variance that potentially results in common method bias seems a problem in our data set. Results of an unrotated principal component analysis to which we subjected all study items show that about 14% is the highest proportion of variance attributed to the first factor. Accordingly, common method variance and, hence, common method bias is not considered a problem.

Scale	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
Complexity (1)	**0.82**										
Insecurity (2)	0.68	**0.76**									
Interruptions (3)	0.60	0.54	**0.87**								
Invasion (4)	0.62	0.72	0.57	**0.78**							
Overload (5)	0.67	0.71	0.71	0.66	**0.81**						
Uncertainty (6)	0.43	0.62	0.41	0.50	0.55	**0.80**					
Unreliability (7)	0.54	0.52	0.63	0.48	0.64	0.44	**0.88**				
Exhaustion (8)	0.49	0.41	0.50	0.42	0.53	0.21	0.42	**0.85**			
Productivity (9)	-0.12	-0.02	-0.04	0.02	-0.01	0.11	-0.04	-0.18	**0.82**		
Active-functional coping (10)	0.19	0.15	0.27	0.14	0.27	0.13	0.26	0.20	0.12	**0.71**	
Dysfunctional coping (11)	0.49	0.49	0.38	0.50	0.42	0.31	0.34	0.43	-0.02	0.45	**0.71**

Table 11: Discriminant Validity According to the Fornell-Larcker criterion

Structural Models

After validating the measurement model, we analysed the structural model to test our hypotheses. Unweighted least squares (ULS) were used as an estimator for the evaluation of the model because ULS perform better with nonnormal and ordinal data as they do not make assumptions about the distribution (Forero et al. 2009). Standard errors were obtained through bootstrapping with 1,000 iterations. We tested the models stepwise: First only the covariate was included, then the IV was added. Next, the mediator variable strain was included and in the last step, the full moderated mediation model set up. The results are displayed in Table 12.

We assessed RMSEA, SRMR, TLI, CFI as indicators of model fit. The χ^2 test statistic is not available with ULS estimation. The absolute fit index RMSEA indicates a good model fit at values smaller than 0.05, just like the SRMR. CFI and TLI indicate satisfactory model fit greater 0.95 and a good fit at values above 0.97 (Geiser 2011). Strict cut-off values were applied to check the suitability of the model, since it has been shown that in ULS estimations, the indices tend not to detect model–data misfit or misspecifications as efficiently as in maximum likelihood (ML) estimations (Xia and Yang 2019). Overall, the moderated mediation model showed a good fit. SRMR was 0.05, indicating only a small divergence between the empirically observed and model-implied covariance matrix. RMSEA was 0.05 slightly above the strict threshold of 0.05. CFI and TLI are indicating a good fit of the model (both, CFI = 0.98, TLI = 0.98) with values higher than 0.97. Even with the strict cut-off criteria, the model seems to fit the data well. Next, we regarded the regression paths of model 4 to evaluate our hypotheses (cf. Appendix D.3 for standard errors and *z* values of the moderated mediation model).

Results of the mediation analysis show that job demands are significantly related to productivity as well as exhaustion. Further, exhaustion is significantly related to productivity. At the same time, the calculated total effect of job demands on productivity ($c = c' + (a \times b)$) was not significant ($c = 0.01$ (0.03), $z = 0.57$, $p = .568$) while the total indirect effect ($ab = a \times b$) of job demands on productivity via exhaustion was significant ($ab = -0.11$ (0.02), $z = -7.61$, $p < .001$). Thus, Hypothesis 1a must be rejected, whereas the results support Hypothesis 1b. Contrarily to our expectations, job demands are positively related to job performance and go along with higher productivity. Furthermore, job demands are positively associated with exhaustion as expected and higher levels of exhaustion go along with lower productivity. When both effects are significant but the indirect effect (*ab*) and the direct effect *c'* point to different directions, we speak of competitive mediation (Zhao et al. 2010).

	Model 1		Model 2		Model 3		Model 4	
	Exhaus-tion	**Produc-tivity**	**Exhaus-tion**	**Produc-tivity**	**Exhaus-tion**	**Produc-tivity**	**Exhaus-tion**	**Produc-tivity**
Intensity of technology use	-0.03*	0.08***	-0.03*	0.07***	-0.03*	0.07***	-0.03*	0.07***
Job demands (TS creators)	-	-	-	-0.02	0.57***	0.11***	0.44***	0.12***
Strain (exhaustion)	-	-	-	-0.18***		-0.25***		-0.25***
Active-functional coping (A)	-	-	-	-			-0.05*	
Dysfunctional coping (D)	-	-	-	-			0.31***	
Coping (A) × job demands	-	-	-	-	-		-0.05**	
Coping (D) × job demands	-	-	-	-	-		-0.12***	
R^2	<0.00	0.01	<0.00	0.03	0.32	0.05	0.36	0.05
ΔR^2	0.00	0.01	0.00	0.02	0.32	0.02	0.04	0.00

Notes. Standardized path coefficients are displayed. Bootstrapped standard errors were used for the interpretation of the results. * $p < .05$, ** $p < .01$, *** $p < .001$

Table 12: Results of the Model Estimation: Direct and Moderation Effects

The direct effect of active-functional coping on exhaustion was significant, as well as the direct effect of dysfunctional coping on exhaustion (see Table 12). The results support the assumptions in Hypotheses 2a and 3a. The use of active-functional coping strategies like support-seeking or actively trying to change the stressful situation is associated with lower levels of exhaustion. In contrast, trying to deal with a threatening situation through denial or consumption of alcohol or drugs to overcome negative feelings is associated with higher levels of exhaustion.

Active-functional coping significantly moderates the relationship between job demands and exhaustion. The negative sign of the path coefficient of the latent interaction term indicates that the negative consequences of DTM use are mitigated. The same applies to dysfunctional coping. The sign of the path estimate for the latent interaction term is also negative. Contrarily to our expectations, the use of dysfunctional coping strategies does not reinforce the effect of job demands on exhaustion but buffers it instead (see Table 12). Hence, Hypothesis 2b is supported by the data, whereas Hypothesis 3b must be rejected.

Additionally, indirect effects were calculated based on the path coefficients and low, medium, and high levels of the two moderator variables ($M \pm 1$ *SD*). This analysis differentiates between the total indirect effect and the conditional indirect effects (simple slopes for each combination of conditions). The results are displayed in Appendix D.4. All combinations of low, medium, and high values for each moderator variable point to the same direction. Coping may reduce the detrimental effect of job demands on exhaustion as well as mitigate the negative impact of DTM use on strain. The analyses also show that the effect of dysfunctional coping is larger than the effect of active-functional coping (compare Table 13)

	Low A (–1 *SD*)	Medium A (M)	High A (+1 *SD*)
High D (+1 *SD*)	-0.07***	-0.06***	-0.05**
Medium D (M)	-0.09***	-0.09***	-0.08***
Low D (–1 *SD*)	-0.12***	-0.11***	-0.10***

Note: Standardized path coefficients are displayed. Bootstrapped standard errors in Appendix D.4 were used for the interpretation of the results of the indirect effects. * $p < .05$, ** $p < .01$, ***$p < .001$

Table 13: Conditional Indirect Effects from the Moderated Mediation Model

Discussion

Our results from the covariance-based structural equation model revealed several unexpected insights. First, besides the negative indirect effect between job demands and productivity (through mediation via exhaustion), there is a positive direct effect. This positive effect means that, with increasing intensity of job demands, productivity rises, which intuitively seems contradictory. This kind of relationship is described in the goal setting theory (Locke and Latham 2002). Difficulties and hard to achieve goals motivate people to do their best for goal achievement until their capability or commitment reaches a limit. Accordingly, a curvilinear relationship between general stress or work pressure and performance is observed (Hofmans et al. 2015; Leung et al. 2011): people who feel fewer demands are not able to utilize their full potential, and productivity is low. With increasing demands, productivity raises until a specific turning point is reached: if employees then exceed this level and the perceived demands are demanded too much, productivity drops. The curvilinear relationship between demands and productivity refers to a rather short period, so there is a temporal aspect. The temporal consideration is reinforced by the fact that long-term increased strain, (i.e., chronic strain), can ultimately lead to burnout (Janssen 2001).

Another reason for the positive effect of job demands on productivity is a potential suppressor effect, which occurs when the direct and indirect effects on a dependent variable have opposite signs and, therefore, an inconsistent mediation is present (Tzelgov and Henik 1991). In the literature, it is considered to be realistic that two opposing direct and indirect effects with similar magnitude almost neutralize each other so the total effect is not significant (MacKinnon et al. 2000). For example, let's take the hypothetical example of workers making widgets, where X is intelligence, M is boredom, and Y is widget production (McFatter 1979). Intelligent workers tend to get bored and produce less, but smarter workers also tend to make more widgets. Therefore, the overall relation between intelligence and widgets produced may actually be zero, yet there are two opposing mediational processes. Therefore, besides the observed positive relationship between technostress and productivity, an increase in demands may simultaneously lead to a higher level of exhaustion, resulting in lower productivity. Hence, we argue that, despite the positive relationship between job demands and productivity, technostress may lead to lower productivity in a long-term view or has no positive impact on productivity. On the other hand, however, techno stressors increase the strain, which can lead to long-term health effects and negatively impact organizational objectives from a long-term perspective. Therefore, technostress should be reduced for organizational and human reasons.

Considering the role of coping for overcoming technostress, our results initially confirm prior research regarding the direct effects: a broad application of active-functional strategies is negatively related to exhaustion. In contrast, a broad application of dysfunctional coping may increase it. In doing so, dysfunctional coping exhibits a stronger direct impact on exhaustion. A possible explanation for this could be the nature of active-functional coping: strategies from the active-functional category (such as actively seeking to change the stressful situation) require individuals' energy and cause cognitive effort in implementation, which, in turn, may reduce the buffering effect on exhaustion.

In contrast, surprisingly, both active-functional and dysfunctional coping reduces the relationship between job demands and exhaustion. Furthermore, we even observed considerably higher values for dysfunctional coping regarding the buffering effect on the relationship between job demands and exhaustion. This implies that even though dysfunctional strategies go along with higher exhaustion, their moderating effect on the relationship between job demands and strain is stronger compared to active-functional strategies. This is particularly interesting because dysfunctional coping is said to be detrimental. The consumption of alcohol or drugs, for example, may lead to long-term adverse effects on physical and mental health (Kahler et al. 2002). Moreover, passive denial of a given situation has been proven to be a concept that is related to the development of depression (Kortte et al. 2003; Naditch et al. 1975) - another reason why dysfunctional coping seems to be a bad strategy to tackle strain.

Nevertheless, these dysfunctional coping strategies seem to help reduce the harmful effects of strain resulting from modern technologies in our sample. The reasons for this relationship emerge when the time perspective is taken into account: coping strategies from the dysfunctional category, such as alcohol or denial of the problem, may result in short-term cognitive and emotional relief. From a long-term perspective, however, alcohol consumption naturally leads to other serious health consequences. The low level of content-related involvement with job demands leads to a reduced competence build-up, which ultimately means that resources are not strengthened. Therefore, we argue that dysfunctional coping, despite its short-term positive effects, would reinforce the consequences of demands in the long-term and, thus, should be avoided for efficiently overcoming technostress.

In conclusion, we see in Table 13 that a broad portfolio of coping strategies consisting of both active-functional and dysfunctional coping reduces the indirect negative effect of technostress via strain on productivity and, thus, also the suppressor effect. This implies that employees who use many different coping strategies from both categories would experience less exhaustion, which ultimately leads to more productivity due to the additional direct effect of demands. On the other hand, the data show that employees with generally few different coping strategies can benefit from the suppressor effect as the total effect of the demands on productivity diminishes. However, they are still exposed to the negative consequences in terms of exhaustion. Employees who focus on a broad portfolio in one of the two categories reduce the negative indirect effects of demands on productivity via strain to such an extent that the positive direct effect of demand on productivity potentially remains significant, although the negative health effects - even if in reduced form - should not be neglected. In this context, it is shown that employees who utilize dysfunctional coping strategies can reduce the indirect effect more strongly, resulting in overall higher productivity, while, at the same time, causing more exhaustion than with active-functional coping, which in turn leads to less increase in productivity. The long-term consequences of dysfunctional copying have already been discussed in the previous paragraph.

Theoretical Contribution

Our research provides three important contributions to research on technostress and coping, namely: (1) investigating the influence of technostress and coping on organizational and individual-level outcomes; (2) modeling coping as a moderator applying the workplace-specific JD-R model as a meta-lens; and (3) emphasize the importance of the distinction between functional and dysfunctional coping of technostress concerning organizational and individual-level outcomes. We will discuss each contribution in detail in die following paragraphs.

In addition to the aspects discussed previously, our research addresses the call by Sarker et al. (2019) that most manuscripts in high-quality journals are concerned merely with the organizational outcomes. In a socio-technical system – i.e., a system focusing on the reciprocal interaction between technology as the technical component and employee as the social component (Lee et al. 2015; Ryan et al. 2002) - it is important to consider both organizational and individual-level outcomes to create synergies (Griffith et al. 1998; Pava 1983; Wallace et al. 2004). Therefore, our research addresses the influence of functional and dysfunctional coping on both organizational (productivity) and individual-level outcomes (exhaustion).

Furthermore, in the context of technostress, we have applied the JD-R model as a theoretical meta-lens, in which both organizational and individual-level outcomes play a key role and which has not been applied in this context before (Bondanini et al. 2020). Thus, in comparison to the transactional model of Lazarus and Folkman (1984), which is usually used in the technostress literature, we applied a model that is explicitly focused on the working context. In the course of this, we have also decided to model coping as a moderator, which has also been applied in recently published studies on coping and technostress (Nisafani et al. 2020; Pirkkalainen et al. 2019) and is in line with the JD-R model. Hence, according to our opinion and recent literature, coping can also act as a moderator and have a buffering effect on the relationship between technostress creators and long-term outcomes. This emphasizes the difference to "coping […] as a mediator of short-term emotional reactions" known from Lazarus and Folkman (1987, p. 147).

In addition to modelling coping as a moderator, we also distinguished the specific nature of coping and examined the influence of different coping styles. Thus, we extend recent literature (Nisafani et al. 2020; Pirkkalainen et al. 2019) which focused on a distinction between proactive coping (i.e., strengthening one's ability to cope) - and reactive coping, neglecting the different types of reactive coping. Dysfunctional coping like the consumption of alcohol or drugs as a reactive form of coping has not been thoroughly investigated. Addiction in the context of DTM use is most salient in the form of behavioural addiction like consumption of pornography or extensive gaming (Tarafdar et al. 2020) while there is less focus on substance abuse. We were able to provide evidence that this aspect should not be neglected in IS research.

Furthermore, we shed light on the role of coping mechanisms used to reduce technostress and, therefore, provide knowledge for the conceptual model of Nisafani et al. (2020) that is in its current form solely covering causal effects of technostress. By doing this, we expand the current knowledge of the existing technostress literature dealing with coping, which is an as-yet less studied research area (Pirkkalainen et al. 2019; Tarafdar et al. 2019).

Overall, technostress research is a highly interdisciplinary field, while it simultaneously is the core of IS research community (Sarker et al. 2019). Such plurality of research perspectives is important to create a deeper understanding of emerging threats due to DTM use. Accordingly, this research activity brings together psychology and IS research by successfully applying the JD-R model for investigating the relationships between job demands, exhaustion, and productivity and examining the role of coping in the context of DTM use. Within our study, we extend the synthesis of these research fields by particularly meeting the recommendations for further investigating the under-researched role of strategies that individuals deploy to overcome strain caused by DTM used in an occupational setting.

Practical Implications

Our results provide valuable insights for practitioners who aim to efficiently meet technostress. Therefore, we extend the recently published conceptual model of work-related technostress by Nisafani et al. (2020) by adding active-functional and dysfunctional coping to the list of existing inhibitors, thus addressing the gap mentioned by the authors. In doing this, we support organizations to better deal with the organizational and individual-level outcomes of using DTMs and provide three suggestions, namely: (1) the appropriate level of demands; (2) the effect of different types of coping strategies; and (3) a categorization of employees with different coping styles.

First, for optimizing employees' job performance, employers should ensure that their employees are exposed to the right level of demands for achieving a high level of productivity. A very low as well as an excessive level of job demands should be avoided. Otherwise, the employee would be under- or overcharged which may result in lower job performance.

Second, regarding coping strategies for meeting technostress, both employees and employers have to carefully deal with the temptations of dysfunctional coping due to the stronger influence on the relationship of job demands and exhaustion: dysfunctional strategies may induce serious consequences in a long-term perspective, e. g., alcohol consumption naturally leading to negative health consequences which disturb employees' life as a whole, or a low level of content-related involvement with job demands leading to a reduced competence build-up. In this context, employers have to be aware of both their economic as well as social responsibilities: they may increase the support for their employees in applying active-functional coping in order to reduce its effort and, hence, increase the beneficial effects of these strategies in overcoming technostress. Simultaneously, even though dysfunctional coping may seem to be an adequate strategy to overcome technostress, it is crucial to convey the fact that other problems, like addiction, could arise in the long run as well. Employers should be aware of this double-edged sword and take preventive measures to identify individuals with risk of addiction. In practice, there are some common measures to identify and support employees with addictive behaviour, e. g., companies and work councils hold regular information events to sensitize both managers and employees to the subject of addiction. Besides, managers should take part in training programs to provide them with the necessary know-how to identify and support potentially addicted employees. Overall, stakeholders like companies, works councils, managers, employees, company doctors, occupational safety specialists, among others, should ensure this is put to practice and promote appropriate handling of dysfunctional coping.

Third, for reinforcing the mitigating effect of coping strategies to overcome technostress, companies should further support their employees regarding their specific coping behaviour: employees who use few different ways of coping should be encouraged to acquire a broader repertoire of various coping strategies for effectively tackling different kinds of stressful situations. At the same time, employees who predominantly use one kind of strategy (active-functional or dysfunctional) are recommended to adopt the other category as well and should be supported by their employer in expanding their respective coping behaviour. In this context, it appears highly important to be aware of the long-term health issues of dysfunctional coping, especially if employees often use dysfunctional strategies (predominantly or in combination with active-functional strategies), employers should ensure to provide know-how regarding these long-term issues by establishing specific health initiatives.

Limitations and Future Research

Besides the provided insights, our study has several limitations that have to be considered. For investigating coping as a moderator, we used a cross-sectional study design where the relationships are based on covariance analysis. Thereby, it is important to note that this does not imply causality. We cannot infer whether dysfunctional coping leads to higher exhaustion from the cross-sectional data assessed at one point in time. Causality may just flow the other way round. For example, individuals who feel exhausted might tend to cope with stressful situations in a dysfunctional manner by consuming alcohol, drugs, or behavioural disengagement, respectively. This would mean that dysfunctional coping is not that dysfunctional at all. Besides, we have looked at coping strategies in general instead of actual coping actions to derive broader findings. In doing so, we took Prinz et al. (2012) as a reference and looked at two possible coping strategies - namely active-functional coping and dysfunctional coping. Although we could already derive compelling contributions and implications from this distinction, a differentiated consideration regarding coping strategies could lead to further insights. Finally, we have focused our analyses only on one component of strain - exhaustion. In addition to this, there are further options such as other burnout facets, absence duration, or general health complaints, which may be taken into account.

To summarize, applying the JD-R model within the technostress context by considering coping as moderating the relationship of technostress creators and strain delivers interesting insights contradicting prior results. For future research, we argue that coping as a moderator should be further investigated. Our results extend current knowledge in the IS in terms of coping for overcoming technostress while arguing for further interdisciplinary studies necessary to provide useful knowledge. In doing so, it might be particularly interesting to provide longitudinal and cross-level designs to investigate the effects of dysfunctional coping. The evidence suggests that causality flows in both directions (Hauk et al. 2019). Behavioural disengagement leads to increased strain, and, in turn, a higher level of strain leads to increased behavioural disengagement at a later point in time. Further coping responses are dynamic und users shift from one strategy to another in the process of coping (Salo et al. 2020), hence it would be interesting to understand coping processes better across time. Furthermore, considering a broader set of different coping strategies could lead to more sophisticated results and enable practitioners to design and support more specific measures to address the negative consequences of DTM use.

Overall, since we successfully put together both IS and psychological stress literature and therefore address the call for further studies proposed by Tarafdar et al. (2019), this research activity enriches technostress research regarding the moderating effects of coping strategies and, building on this, further studies which examine coping as moderating the effects of technostress on various outcomes are highly recommended.

5. Designing Digital Technologies and Media to Promote the Health of Employees

In the two previous chapters, different aspects of technical and social components were examined, influencing the reciprocal interaction, and instrumental and humanistic outcomes. This helps to design the digital workplace as a socio-technical system to ensure the two components are in harmony. Another alternative to promote the employee's health could be to consciously use DTMs to better adapt to the needs of the social component. Thus, the technical component can either promote its reciprocal interaction with the social component or promote the reciprocal interaction between another technical component with the social component. Several IS researchers have made explicit calls for developing neuro-adaptive IS, which recognize the user's neurophysiological state and positively adapt to it (Riedl 2012; Vom Brocke et al. 2013). For example, Adam et al. (2017) propose a simple design blueprint for stress-sensitive adaptive enterprise systems (i.e., systems that aim to mitigate stress by applying intervention measures to the social and technical components). However, a primary challenge in building such systems is the reliable assessment of employee stress. Therefore, DTM sensing capabilities need to enable a mobile-based, data-driven approach using user, environment, and user-environment interaction data. Various instantiations have already demonstrated such systems' feasibility for different application scenarios (Gimpel et al. 2015, 2019b; Lane et al. 2011; Lu et al. 2012; Wang et al. 2014). However, these systems have many commonalities, such as those regarding their architecture, and, yet, general guidelines on how to design mobile stress assessment systems do not exist. As a result, the research within this chapter focuses on fostering the fit between the technical and social components by designing DTM so that they adjust accordingly to social components' needs, ultimately, to support the achievement of instrumental and humanistic objectives. More precisely, this dissertation provides knowledge on DTM designs that support users in applying stress management techniques and building the foundation for stress-sensitive systems. Section 5.1 presents prescriptive knowledge in the form of a framework regarding the design of DTM that collect and store data on the user and her/his environment. Research in Section 5.2 presents descriptive knowledge from the experience of developing a prototype for life-integrated stress assessment applying the framework from the previous section. Finally, Section 5.3 presents prescriptive knowledge contributing to a design theory for mobile stress assessment based on experiences with the Section 5.2 developed prototype and the already existing knowledge from the literature. Major parts of Chapter 5 conform with Beckmann et al. (2017), Gimpel et al. (2019b), Bonenberger et al. (2020).

5.1. Designing a Sensor-Based Data Collection Framework

Before such technical components, as described in the introduction to this chapter, can be designed and developed, the necessary foundations for these systems must first be laid. The first step is to enable the technical component to collect data about the environment and the user. As mentioned in Section 3.2, more and more users are collecting data about themselves and their environment to learn more about their lives and evolve. Despite the already shown potential, most DTM users do not collect and process personal data (Van Der Wal, Ariën J and Shao 2000). Yet it is this data in particular that is suitable for smart living or to improve personalized health of an individual by the usage of Internet of Things and its connected data. Here sensor fusion represents the possibility of personalized healthcare, based on the variable choice of used devices. In the medical sector sensor fusion can be deployed in three different application fields. Most common area is clinical sensor fusion in hospitals within Medical Application Platforms (Hatcliff et al. 2012) for concurrently smart monitoring patients' various health values. In addition, sensor fusion can be used in domestic telemedicine or telerehab in combination of Internet of Things of Medical Devices (IoTMD). Closely associated is the wellbeing and prevention area, which also appears in combination with IoTMD and Smart Homes. This area represents the most potential and also the most risks of personalized healthcare, since prevention is highest affected by individual's health needs. A personalized medical Smart Home which is using sensor fusion requires different devices, for instance, wearables, nearables and sensors for each patient's medical precondition. However, this fact represents one of the most complex issues of sensor fusions. Devices are heterogenic and difficultly combinable.

We address the above-named issue by developing a generic medical sensor framework that is able to combine sensors and collect data independent of devices. Through this solution, we make sensor fusion generic, thus enable personalized health needs and the usage of desired sensors. Furthermore, we offer continuous measuring, including collecting data and enable further processing. In this way, it is applicable to several health monitoring use cases. The potential for utilizing a framework for generic medical sensor fusion was recognized by many research approaches. For example, the authors in (Couderc and Kermarrec 1999) proposed an infrastructure based on contextual objects in distributed client/server IS, whereas (Dey et al. 2001) developed a toolkit for context application programming. Furthermore, the FUNF framework (Ranganathan and Campbell 2003) is capable to acquire data over third-party sensors, supporting different transmissions protocol and the Open Service Architecture for Sensors (OSAS) framework, an event-based programming system for sensor networks. In contrast, our solution differs through the fact that we use physiological data of patients and combine these with ordinary sensors and medical sensors, and minimize limitations of personalization through unbounded sensor choice.

As already mentioned, digitalization brings many opportunities. However, these opportunities also involve challenges. The increasing usage of information technology in business and private life negatively impact health, e.g. stress. Individual stress sensitivity represents an example for a personalized wellbeing and prevention use case. We avail our use case “Stress Detection and Prevention” for the concluding evaluation. Therefore, we will discuss three main theses including the functionality of our framework and the successful personalized stress monitoring. In addition, it will be shown that sensor fusion-based data offer more potential for healthcare improvement than single sensor-based data. Along with this we can reveal the health improvement potential of the combination of ordinary sensors and wearables.

The remaining Section 5.1 is structured as follows: After introducing our approach for a personalized healthcare sensor fusion we present our Java Data Collecting Framework (JDCF). The architecture, components and functions will be shown. Afterwards we evaluate the framework in terms of proper functionality and health improvement by conduction an experiment using a stress game.

Java Data Collection Framework

Today, there exist a great variety of sensors in the healthcare sector. Lee et al. (2008) categorize sensors used in healthcare monitoring systems according to their spatial distance to the patient. 1) Medical body sensors like heart rate monitors, the closest to the individual, 2) environmental sensors e.g. room temperature sensors and 3) location sensors like indoor relative localization receiver more and more move further from the patient. More generally we can differentiate sensors by their transfer medium e. g. wired or wireless, their behavior e. g. active or passive or their type to deliver data e.g. time or event-based. Typically, these sensors represent a specific view and partial model of the patient and his environment. To increase the rate of integrity, more and more data in healthcare systems is collected. On top of this, several sectors exist that enable the usage of sensors. However, sensors which are traditionally not used for the assessment of various information about the user’s health (e.g., keyboard, mouse), can provide important aspects of the user’s current behavior and hence also with his current physiological or psychological state. This information, acquired by different sensors and devices with diverse initial purposes, is used to build, for example, individualized IS that adapt themselves according to the user's needs (Adam et al. 2017). However, because of its manifold use of application, it requires a highly generic approach to provide this system with the gathered information, independent of the underlying technology and inherent workflows.

The ease of deployment, data acquisition efficiency and application layer challenges as "one of the hardest challenges" in healthcare systems (Alemdar and Ersoy 2010). Especially the huge number of different sensors, results in a big challenge for systems to assess, process and store these data. Having different kind of sensors, the need of a scalable and flexible data persistence increases. In particular, the data persistence (e.g. database, file) can vary or dynamically change depending on the usage. To cope with these challenges generated by this diversity of sensors, we aim to develop a framework that connects multiple sensors and achieve the combination of different ways of data persistence regardless where the sensor is located or how it is connected. Hence, we developed the JDCF that is capable to assess data and information from different types of sensors and provides this value resources for further systems by storing this information in various data spaces, called persistence forms. JDCF enables an easy way to log all kind of data by the usage of Java objects and change the persistence form easily to address challenges.

In a classic input-process-output point of view JDCF is placed in the middle of two interfaces (Person & Environment and Usage). In Figure 13 we present JDCF as the connecting part between multiple sensors on the left-hand side (Connection) and different persistence forms on the right-hand side (Persistence). In the first place we describe JDCF on a high abstraction level and go into technical details afterwards.

We developed a five-phase approach from a specific sensor, connected in a personalized healthcare system, to the usage of its collected data. The three middle phases represent JDCF. Every step in this simplified process has its own challenges JDCF helps to overcome through a highly-generic software architecture, called the JDCF data flow:

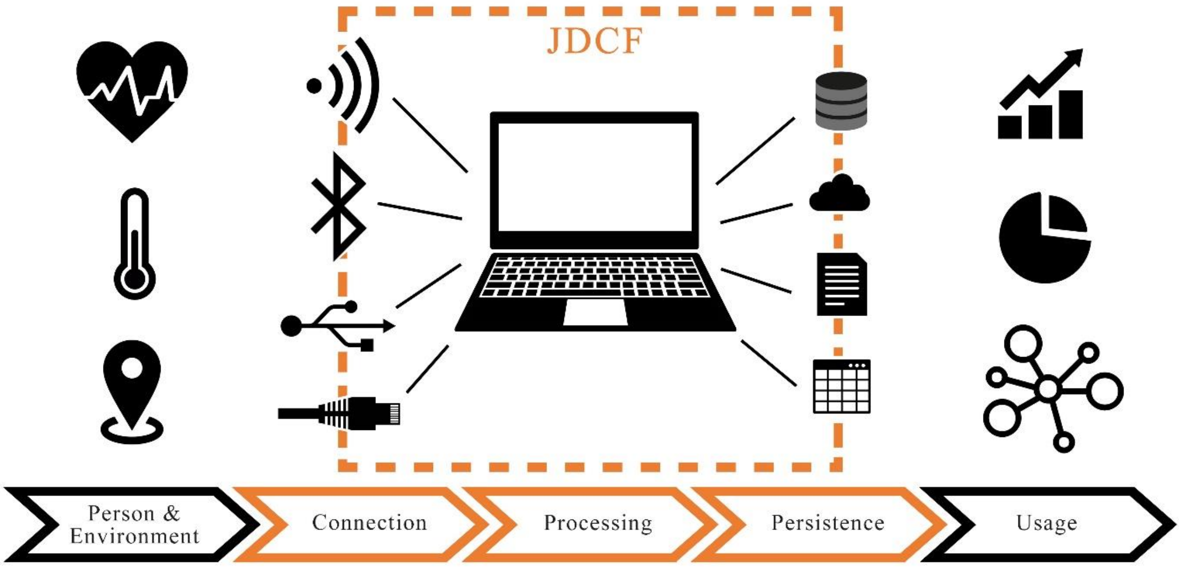


Figure 13: JDCF Data Flow

Person & Environment: Tracking the physical or psychological state of a patient e.g. stress, involves a great number of sensors. Since this amount is not static, applications need to be scalable and should allow new, maybe yet unknown, sensors or sensor networks to connect easily. This represents the precondition of JDCF utilization.

Connection: Requiring different kind of sensors, the integration into healthcare systems gets more difficult. JDCF enables to easily connect miscellaneous sensors by providing generic interface place holders to implement existing drivers, libraries or frameworks and integrating these in the data-flow within JDCF to conduct sensor fusions.

Processing: The development of new applications for personal healthcare can be divided in two main challenges: 1) implementing new modules or algorithms to scientifically assess physiological issues and questions as well as 2) building up the software-technical infrastructure to receive the relevant data. To reduce the effort to master these, JDCF delivers a unified but generic data-flow between a sensor and the selected type to store its data or information. Thereby the developer is able to select the type and granularity of the data to be collected as well as the type of the persistence. Furthermore, he has the possibility to simply connect new, not yet implemented, sensors or kinds to store their data. Using existing interfaces and abstract classes allows the integration of new components in the JDCF data-flow.

Persistence: Inconsistent and heterogeneous data pools are time-consuming for further processing (e.g. medical sensor fusion application). Moreover, every preprocessing step to increase the data homogeneity can result in a loss of data quality. Using JDCF helps developers to receive structured data and to store these in dissimilar persistence forms. Beyond the generic persistence structure, we achieved our aim of allowing the connection of new persistence forms. This means it is possible to change the type of persistence on demand. Thereby JDCF can react on a heterogeneous IT-environment just like it is needed in healthcare systems e.g. an application for electronic devices to monitor patients in emergency departments or a personalized health platform to assess stress.

Usage: Especially in personalized health platforms it is mandatory to use existing data for different analyses. Transforming semi-structured data in heterogeneous persistence forms normally implies a costly overhead and a poor system performance. A sensor integrated in the JDCF data flow can have multiple equal forms of data output as well as different persistence forms. Hence, JDCF enables through a generic persistence structure a quantity- and type-independent reuse of the collected data. Using e.g. the heart rate data as a part of a stress detection model has no negative effects on creating a dashboard for cardio-activities.

A practical demonstration of these 5 phases is offered in the next subsection. In general, this framework supports personal healthcare developers throughout the whole process from sensor-binding to data persistence. It also enables an easy way to log all kind of data and dynamic changes in the persistence form. As well, JDCF can be used by multi-users without violating privacy rules, since it is a self-hosted framework which stored data locally. To further detail the processing of JDCF, we explain the data flow of collected sensor data and go increasingly into detail on the way through JDCF (Figure 14) as far as possible at this point. More details are out of scope.

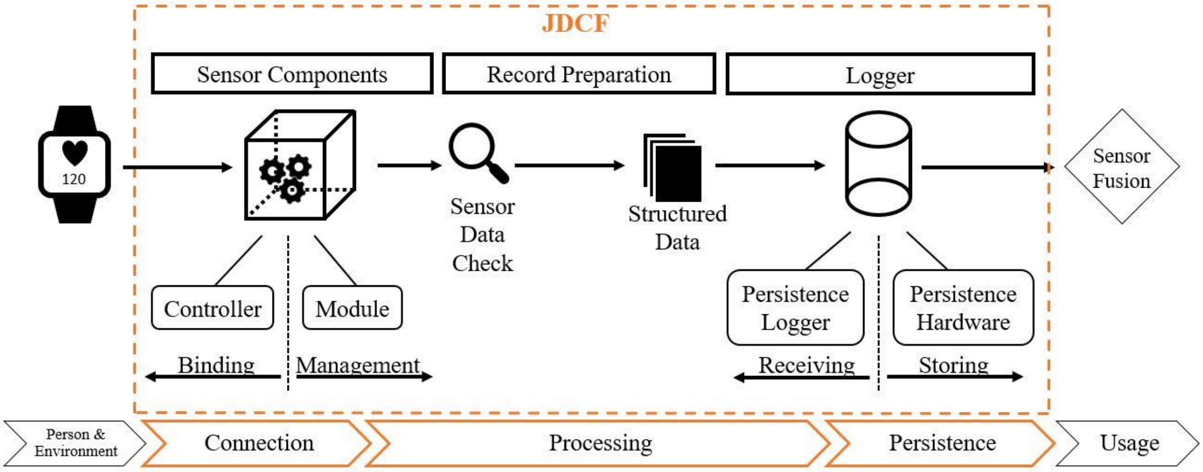


Figure 14: JDCF Components

Sensor Components: Every sensor in JDCF uses its own SensorController and SensorModule. The main task of the SensorController is the binding between JDCF and the sensor. Therefore, JDCF offers an interface placeholders which can be used by the sensor. The controller enables the usage of external libraries and every other customized implementation to receive data. The SensorModule includes the whole managing part to enable or disable logging or activating/de-activating the sensor connections. This allows very easy handling of the sensors. Furthermore, JDCF offers two different standardized types of controllers and modules. On the one hand event-based sensors, which trigger the controller for new data during events of the hardware sensor and on the other hand time-based sensors that trigger the hardware sensor for new data in a certain time interval. All necessary components like time management for time-based sensors are already included in JDCF. Regardless of the type we use, the controller is the executing point when the sensor is triggered. Every time the controller is executed a new SensorRecord will be created. The SensorRecord is a central object of JDCF which includes the whole received data of one sensor at one receiving moment with a unique identifier and the time of creation.

Record Preparation: Theoretically, a single sensor can give different and unsorted data. To assure the received data is in a sorted structure, every sensor implements its own Sensor-RecordStructure which determines the data type with enumerations. This structure includes the regulation for data sequence and datatypes for every sensor. The framework includes control mechanisms for every Java object to respect this structure by monitoring every incoming data value. By the usage of generic Java objects data can be stored type-independent. The Sensor-Record considers the structure during the creation. In case of not considering the structure JDCF throws a SensorRecordStructure Exception. Thus, a data validation is conducted. The self-checked and correctly filled SensorRecord is send to the Logger.

Every *Logger* is a special type of the JDCF PersistenceLogger. Since there are different forms of persistence, it is important to allow a generic saving of the data. JDCF provides the needed specifications for the logger to be implemented. Due to the information contained in the structure, each logger has all the necessary information to store the data. Thus, every single implemented PersistenceLogger is enabled to log correctly based on the SensorRecordStructure included in every SensorRecord.

To manage several sensors at the same time as easy as possible, we need a solution, holding the SensorModules. Therefore, JDCF contains the SensorManager. It opens the possibility for holding multiple sensors named by a central enumeration. This enumeration is mainly responsible to easy access the sensors by their names and assure there are no duplicates. Furthermore, the user can create multiple sets of sensors by creating multiple enumerations for the SensorManager. This enables the partition of sensors by their use case or type. This implementation of JDCF makes it possible to access any sensor using the SensorManager in combination with the central enumeration. The maximum number of processible sensors in general, is only limited by the available resources of the used hardware for JDCF.

A summary of the described elements of JDCF is provided in Table 14. After we presented JDCF, we are going to demonstrate our approach with a stress study. This is followed by practical handling and evaluation of the results.

Name	Short Description
SensorModule	Contact partner for managing a sensor
SensorController	Connection to the hardware sensor. Executed to create new SensorRecord
SensorManager	Container of SensorModules in combination with an enumeration for easy access
SensorRecord	Sensor data containing the result of a single controller call with an id and timestamp
SensorRecordStructure	Regulation of the sequence and datatypes for sensor data

Table 14: Elements of JDCF

JDCF provides developers of sensor environments with different structures to facilitate the collection, processing, and storing of acquired data. However, to satisfy the intended purpose and the consideration of legal rules (e.g., data privacy and security) and moral principles (e.g., confidentiality of information) is within the user's range of tasks.

Evaluation

To evaluate our framework, we conducted an experiment using JDCF to perform a sensor fusion, gathering and preprocessing data. For this experiment, fifteen participants played a stress game (Schaaff and Adam 2013), which puts participant under stress by inducing different stimuli. Therefore, the game involves two phases; the "low-arousal-mode" and "high-arousal-mode". In each phase different human senses (e.g. audio, visual) are addressed to induce stress. Through correct or wrong user answers a score resulted. In addition, a high score list was visible during the whole experiment to induce social comparison and, thus, stress. The participant's physical condition (e.g. skin conductance, heart rate variability) is essential for the subsequent stress analysis. Hence medical sensors were integrated into the framework. The participants wore a self-tracking band which had to be attached a certain time before to be calibrated with the skin. Additional, during the game, data from mouse, keyboard and the self-tracking band was collected via the framework. Moreover, we further log the rate of accurate statements in order to assess the user's current stress level. All generated data were collected and preprocessed by JDCF. Afterwards we analyzed these data to train the analysis algorithm whether the user is stressed or not. This knowledge can be used in future real-time stress analyses. In addition, we observed the result's impact of medical and non-medical sensors. Regarding the principles of Monte-Carlo-simulations, the order and distribution of training and test data were randomized. For example, we evaluated (non-) stressed-states and measurements with solely technical or medical input data and combined measurements. On average the accuracy for assessment of the user's stress level for all non-stressed-states is about 99% and for all stressed-states about 70%. A higher accuracy can be achieved through a bigger learning data set. The "arousal-modes" were used as verification. Within the evaluation of the model we also determined the influence of every factor measuring the probability of a decent prediction. For instance, excluding the skin conductance data decreased the accuracy by 5.1%. Similar, not considering the skin temperature data meant a decrease by 4.9%.

In summary we were able to successfully apply the framework that enabled us to combine individual chosen sensors and to gather data. Afterwards we were able to determine a person's stress level. As a result of the experiment, we were capable to verify our approach and to substantiate that combining different data with sensor fusion improves the accuracy of an assessment whether a user is stressed or not.

Conclusion

As demonstrated the framework supports collecting and combining heterogeneous data in the area of individual health management. Furthermore, the framework can be used in the other medical sectors, e.g., medical application platform and telemedicine. Depending on medical applications, analyzing represent a complex challenge. Thereby data of diverse kinds need to be handled. The proposed framework manages to handle varying datasets by implementing every issue as a single sensor enabling various ways to save, combine and analyze them. Telemedicine or rehab represent the idea of clinical health care at a distance. Thereby, verifying the accurate execution of rehab exercises is a huge challenge. JDCF can simplify this task by integrating the mobile phone as sensor. By holding the phone within the execution of exercises the patient data will be collected via the framework and can analyze the efficiency of exercise afterwards. Recently, an executable version for android is tested to enable JDCF to run on the mobile phone itself for further flexibility concerning location and time. Hence, the functionality of JDCF will be proven in further different use cases, while refining the system itself with every single instantiation.

We presented JDCF, a generic medical sensor fusion framework, which simplifies collecting data from different sources and combine arbitrary sensors in a consistent way. The architecture and components were described, as well as functionality and versatility. We exemplary demonstrated the usage and functionality of JDCF by assessing the stress level of a user during a self-advanced stress game. The collected data were reprocessed with data-analytics techniques to recognize stress symptoms. We were able to prove the applicability of JDCF, the stress detection and the added value of medical sensors in stress assessment by excluding gradually sensors and showing the decreasing accuracy. As JDCF is able to generically integrate seamlessly new sensors, it is qualified to be used in different fields of health care or other personalized life science applications.

5.2. Developing a Prototype for Life-Integrated Stress Assessment

In the previous section, the basis was laid that enables the technical component to collect data about the environment and its user. Building on this, DTMs can now be developed that assess the user's psychological state with the help of the collected data. If this is feasible in a reliable way, the technical component can later be adapted to the social component. Accordingly, this section develops a mobile life-integrated prototype based on the JDCF to assess stress, which is one of the most prevalent and discussed health problems of our time (Riedl 2013). Originating from the general rise of complexity and mental load in business and private life, the number of people regularly experiencing stress is increasing (Ferreira et al. 2009). This is an individual and societal, but also economical problem, as stress can induce unhealthy behaviour (e.g., alcohol abuse, smoking) and is the main cause of psychological and physiological illnesses including burnout (Goh et al. 2016). First efforts towards technological support of stress management and coping have recently been launched in both science (Adam et al. 2017) and practice (Soma Analytics 2017).

This is enabled by today’s omnipresence of powerful sensors incorporated in DTMs like, for example, the smartphones or other smart things, which significantly facilitates the access to sensory data. The vast amount of data produced by smartphones’ rich sensing capabilities opens the path for sophisticated technological and informational assistance of individuals – a field, which is gaining increasing attention in IS research (Hess et al. 2014; Legner et al. 2017) and contributes to environmental sustainability (Tiefenbeck et al. 2019) and individual health (Lane et al. 2010). In combination with progress in the field of artificial intelligence, this can lay the foundation for DTMs that use sensors and actuators to adapt to the individual user (Dey 2016) in order to serve humanistic (e.g., well-being, health, enjoyment) and instrumental goals (e.g., performance, productivity). DTMs focusing on the sensing of psychological parameters such as emotions, well-being, or stress commonly run under the term “affective systems” and provide significant advances in the detection of human affection (Marreiros et al. 2010; Moore et al. 2014). Recent efforts, for example, include intelligent help provision (Friemel et al. 2018), enhancements in personalized healthcare, technological support of health prevention (Nahum-Shani et al. 2018), or the design of stress-sensitive adaptive enterprise systems (Adam et al. 2017).

Resulting DTMs designed to help users dealing with stress range from functionally limited end-user applications that assist in the application of stress management techniques (e.g., the real-time recommendation of appropriate coping mechanisms) to the theoretical conception of enterprise systems that automatically adapt their user interfaces and workflows to the user's cognitive state (Adam et al. 2017). Next evolution steps could be personalized stress-aware user interfaces, safety measures in human-machine interaction, or mobile apps recommending appropriate activities based on the individual's stress level, for example, a relaxing visit to the nearby spa. DTMs sensitive to stress require useful input data. However, sensing and evaluation of psychological factors like stress are hard to put into practice: Accurate physiological measurements often require bulky hardware (e.g., electrocardiography) or people's physical presence at a specific location. Thus, they are not applicable for use cases, which require a continuous stream of sensory input, like location-independent adaptive stress interventions.

To overcome these problems, Fischer and Riedl (2019) recently proposed the idea of lifelogging for organizational stress, which suggests that DTMs can be used to unobtrusively and continuously collect data on an individual and a situation. Various approaches have already emerged that use smartphone data to get information on the user's behavior or environmental context (Lane et al. 2011; Lee et al. 2012; LiKamWa et al. 2013). Although these DTM-based approaches are outperformed by physiological measurements regarding quality and accuracy, their broad range of sensors and good integration into people's daily routines can make the assessment of unconscious mental processes widely accessible and applicable (Dimoka et al. 2011). This paves the way for the design of adaptive DTMs, which continuously sense the individual's mental state and execute regulating measures like adapting the interface or organizational workflows accordingly to better fit the user's needs.

Most use cases call for a fully automated recognition of stress that does not need direct user interaction. However, existing approaches to stress assessment require the user's attention or even collaboration by means of questionnaires or behavior change. In the research within this section, we aim at full life integration of smartphone-based stress assessment without user cooperation and collect real-life evidence for its feasibility. This also excludes the use of wearables such as fitness trackers or smartwatches, which – despite their growing prevalence – for many people still feel unnatural in permanent use and, thus, might not be appropriate for continuous measurement. We follow standard design science research methodology (Hevner et al. 2004; Peffers et al. 2007) to investigate the following design objective (DO):

DO) Design and develop a life-integrated mobile DTM that is capable to continuously assess a user's stress level without influencing the user's daily habits at all.

The proposed DTM uses various hardware and software sensors to collect data on both behavior and environmental context associated with common stressors and strains. It is prototypically instantiated and evaluated in a public field study. In comparison to existing prototypes, it does not interfere with the user's perceived routine constraints such as wearing an unfamiliar device (e.g., wearable) or changing the user's daily routines (e.g., requiring a second smartphone or additional daily actions) (Buchwald et al. 2015). The prototype helps to demonstrate the general feasibility of life-integrated continuous mobile sensing and its generality for the assessment of perceived stress. An analysis of the data gathered within the field study yields a universal stress assessment model, which links data from smartphone sensors to stress valuation and confirms the operationality of life-integrated, continuous, mobile stress assessment. Lessons learned during the development process give valuable insights into the development of stress-sensitive and stress-adaptive DTMs that respond to the user's stress and provide targeted technological or situational stress management interventions.

This section follows a structure similar to the publication schema suggested by Gregor and Hevner (2013): The following subsection recaps the background on both the physiological and psychological nature of stress and reviews related work on the mobile sensing of psychological factors. We then shortly outline the research setup and describe prototype and prototyping process, in which we learned that efficient resource consumption and privacy are even more important for applications that run unobtrusively in the background. The evaluation of data collected within the public field study yields a person-independent classification model that predicts stress as a binary variable with an accuracy of 81 %. A regression model built with the same data distinguishes stress levels between 0 and 16 with a mean absolute error of 2.12 in a cross-validation scenario and explains approximately 41 % of the variance in stress. We further demonstrate that the personalization of the model can significantly improve model accuracy, conclude with a discussion of the implications and limitations based on lessons learned during the prototyping and evaluation process, and provide an outlook on future research.

Theoretical Background

Stress is a highly complex and individual phenomenon, which is strongly dependent on the interaction between a person and its environment. Based on this, we derive two essential aspects that influence the design of our system. First, the evaluation, whether a situation is perceived as stressful or not, is performed mentally. Consequently, our system cannot assess the actual stress of a user but must rely on assessable information. Therefore, we require data from sensors that conclude potential stressors (e.g., humidity, noise, number of messages) or strains (e.g., changes in voice, tipping behavior). Second, stress is dependent on the interaction between a person and its environment. Hence, it is necessary to gather information on both the user (e.g., behavioral data) and their environment (e.g., temperature, humidity).

Today, smartphones are our daily companion. They feature an increasing number of hardware sensors (e.g., air pressure sensor, humidity sensor, and accelerometer) and collect valuable information, which might give an indication about the user's mental state as suggested by several researchers. To analyze relevant application scenarios, we conducted an extensive analysis of mobile sensing use cases, which builds on three comprehensive reviews of the literature on mobile stress assessment published by Aigrain (2016), Greene et al. (2016), and Þórarinsdóttir et al. (2017). We complement their list of studies by searching in the AIS Senior Scholars Journal Basket (MISQ, ISR, JAIS, JMIS, EJIS, ISJ, JSIS, JIT) and all outlets of the IEEE Xplore. Our search has been limited to research articles on the assessment, detection, determination, or recognition of stress using IS or DTM in the context of human, people, user, or individuals by using multiple search strings based on these terms. We consider only studies from 2010 and later because stress detection gained substantial attention only since then. We found that several researchers have already exploited this data source for recognizing human psychological conditions in various ways: (1) assess stress via only a smartphone, (2) assess stress with several different devices (e.g., two smartphones or a smartphone plus an additional device such as a wearable), and (3) recognize not stress but emotions, mood, or activity (e.g., walking, running, cycling) with similar measurement techniques. The following paragraphs address these categories sequentially.

Research assessing stress using a single smartphone is rare. A literature review revealed only two applications that perform this task, both originating from the same research institution: BeWell (Lane et al. 2011) and StudentLife (Wang et al. 2014) are Android applications that assess the smartphone user's stress level by tracking activities that affect physical, social, and mental well-being. The relevant data is collected by continuously reading several smartphone sensors including the microphone, accelerometer, and light sensor. BeWell extends this data by integrating additional user information entered through a web portal. StudentLife pushes multiple questionnaires to the smartphone, which must be answered by the user, and extends the collected data using location-based information within the research institution's facilities (e.g., the traveled distance inside buildings based on Wi-Fi logs). However, both applications require the user to answer multiple (an average of eight) questionnaires daily, which serve as an additional data point and are not only used for model training purposes. This makes these systems rather obtrusive. Bauer and Lukowicz (2012) identify longer stressful periods, e.g., exam weeks, from smartphone usage but do not directly assess stress.

Several applications assess stress with a smartphone plus additional DTMs. While both Ferreira et al. (2009) and Kocielnik et al. (2013) use external DTMs to measure body reactions (e.g., increased sweating, rapid heartbeats), Sano and Picard (2013) attempt to recognize stress with mobile DTMs, a wrist sensor, and several daily questionnaires. Equally important, Lu et al. (2012) measure stress by analyzing the human voice and use a second phone to distinguish between speakers. Most of these applications do not enable the continuous assessment of stress, except for Kocielnik et al. (2013).

DTMs related to stress assessment include emotion, mood, and activity detection systems. Most DTMs that aim to assess these conditions use exclusively smartphone data. The only exception is Choudhury et al. (2008), who use an external DTM to measure additional parameters (e.g., humidity). This data can be enriched by additional user input (Chang et al. 2011; LiKamWa et al. 2013) or gathered unobtrusively (Albu et al. 2008; Rachuri et al. 2010). In this category, Choudhury et al. (2008) and Lee et al. (2012) do not achieve a life-integrated assessment, because the former uses an external DTM with extra information, and the latter uses a customized Twitter app instead of the original app.

In general, different research projects have shown the feasibility of basing assessments of stress or stress-related psychological factors on the human voice (Chang et al. 2011; Lee et al. 2012), sleep (Lane et al. 2011; Sano and Picard 2013; Wang et al. 2014), social interaction (Bauer and Lukowicz 2012; Wang et al. 2014), location information (Lee et al. 2012; Rachuri et al. 2010), ambient information (Lee et al. 2012), body reactions (Kocielnik et al. 2013), activity recognition (Choudhury et al. 2008), and behavioral patterns (Ferreira et al. 2009; Kocielnik et al. 2013; Lee et al. 2012; LiKamWa et al. 2013). Furthermore, the unobtrusive mobile sensing of different parameters on a single smartphone (Lee et al. 2012; Rachuri et al. 2010), which is recommended to obtain less biased data (Lee et al. 2014), is possible. Moreover, the related work shows that the continuous sensing and assessment of the user's mental state (Lee et al. 2012; Rachuri et al. 2010) is realizable, especially for emotion, mood, and activity detection (Ferreira et al. 2009; Kocielnik et al. 2013; Lee et al. 2012; LiKamWa et al. 2013). Furthermore, the unobtrusive mobile sensing of different parameters on a single smartphone (Lee et al. 2012;

Rachuri et al. 2010), which is recommended to obtain less biased data (Lee et al. 2014), is possible. Moreover, related work shows that the continuous sensing and assessment of users' mental states (Lee et al. 2012; Rachuri et al. 2010) is feasible, especially for emotion, mood, and activity detection.

We found that the required level of interaction with the individual, which ranges from significant restrictions up to full integration into users' daily routine, is one of the main differences between stress assessment approaches. To the best of our knowledge, none of these DTMs provides a life-integrated and continuous assessment of perceived stress without interfering with the user's perceived routine constraint. In prior research (Gimpel et al. 2015), we devolved a prototype to assess perceived stress using smartphone sensing techniques. In this research, we extend the prior work-in-progress by presenting the final prototype, refining the development process and providing full data analysis of the field study.

Research Process

Our research follows the standard design science guidelines by Hevner et al. (2004) and applies the design science research methodology (DSRM) by Peffers et al. (2007), which suggests that each design science research project performs the following six activities: (1) identify the problem and motivate, (2) define objectives for solution, (3) design and develop, (4) demonstrate, (5) evaluate, (6) communicate.

Problem Identification: Modern DTMs (e.g., adaptive systems) and ubiquitous sensing capabilities (e.g., in smartphones) can help to provide new solutions for the individual, societal, and economic problem stress (e.g., stress-adaptive DTMs).

Objectives: Design and develop a life-integrated mobile system that is capable to continuously assess a user's stress level without influencing the user's daily habits at all.

Design & Development: Stress theory lays the foundation for DTM design and the selection of appropriate smartphone sensors. Other DTMs in the context of mobile sensing, affective computing, and stress assessment provide further inspiration for the artifact. Building on this foundation, we conceptualize a mobile DTM that continuously gathers data about the user and its environment from stress- and strain-related smartphone sensors. The acquired data will be trans-formed and employed to assess the user's stress level by identifying patterns and correlations between sensed data and perceived stress.

Demonstration: The proposed DTM has been prototypically implemented for the Android platform. The prototype helps to demonstrate technical feasibility (operationality and effectiveness), obtain user feedback (ease of use), and collect comparative data (generality) to test the accuracy of the stress assessment analysis process (Sonnenberg and Vom Brocke 2012). First releases of the prototype were provided to a selected community of alpha and beta testers before releasing a stable version.

Evaluation: To evaluate the model, we employ the prototype within a public field study to foster the results for the generality of our prototype by achieving a high external validity of the results. From that, we derive a statistical model for perceived stress solely based on data from smartphone sensors. Together, prototype and statistical model show the design's conceptual and practical feasibility regarding operationality and effectiveness as well as the practical utility of life-integrated and continuous mobile stress assessment, considering the ease of use for the prototype's users.

Communication: Finally, we communicate our research in line with Gregor and Hevner (2013). A preliminary version of this research has already been presented at a conference (Gimpel et al. 2015), while it was still in progress, but did not yet include data analysis and evaluation. Valuable feedback from the research community was integrated into the design and presentation of the results.

Prototype

Requirements

Based on design objective and related work, we identify three relevant requirements: (1) life integration, (2) assessment continuity, and (3) abidance to non-functional requirements for medical mobile systems.

Life-Integration: To minimize intruding effects and reduce bias, the DTM needs to be fully integrated into the user's life, i.e., it must not be perceived as an additional stressor or interfere with the user's perceived routine constraints. Studies have also highlighted the stress-inducing aspect of questionnaires (Intille et al. 2003; Scollon and Kim-Prieto 2003). Moreover, periodically appearing questionnaires are likely to stress people and can consequently bias the assessment. Thus, users must not be explicitly and regularly surveyed on their current stress level (except for model alignments, which should be used rarely).

Continuity: Stress varies over time, potentially in short cycles. As appraisal steps permanently (re-)evaluate stressors to determine stress, it is crucial that the DTM must be capable of grasping changes in the person's current situation. Thus, the DTM must deliver a plausible assessment of the user's current stress level whenever requested to allow for effective intervention and adaptation. In future, we aim to perform computations directly on the smartphone and limit the use of internet services.

Medical mobile non-functional requirements: The European Commission (2015) published a Code of Conduct on privacy for mHealth apps, which addresses the problem of the often discussed privacy concerns on mobile apps (Gimpel et al. 2018a), particularly in the health context. This code further provides guidance to app developers and publishers regarding the display of certain application practices information. Hence, in order to provide a high level of quality, the system must adhere to the medical mobile non-functional requirements presented by Meulendijk et al. (2014): accessibility, certifiability, portability, privacy, safety, security, stability, trustability, and usability.

Prototypical Instantiation

The assessment of stress using life-integrated smartphone sensing requires a user-centric development process. In several development and deploy cycles, we developed and continually evaluated an Android prototype. Six alpha tester (the authors and three testers outside the research team) provided feedback that helped to refine the prototype and create a more mature artifact prior to releasing the app to a larger beta testing group. This group consisted of 8 participants with different smartphones and different operating system versions. Feedback from beta testing helped finalize the application as a ready, multilingual app (German and English) that could be used within a global field study without major constraints on the device or operation system version. The lean user interface (Figure 15) has been designed together with usability professionals. The prototype embeds into a general architecture consisting of four major components: 1) The smartphone user and their surroundings, 2) the smartphone's hardware sensors as transitions between the social and the technical part of the system, 3) the prototype capturing sensor data and periodically uploading it into a cloud storage, and 4) model building of a stress assessment model.

The application is designed to read 38 hardware and software smartphone sensors in order to empirically identify sensors that might be valuable for stress assessment. These sensors are the outcome of a conceptual evaluation of available smartphone sensors and the unobtrusive smartphone-based measurability of stressors and strains from the TMS. Here, we focus on sensors that can provide us with information on either the user or their environment. For this purpose we rely on information from hardware sensors to determine parameters of the environment (e.g., temperature, noise, location) and software sensors (i.e., using sensor fusion to process multiple basic information to more com-plex information) to collect behavioral or environmental data (e.g., typing behavior, sentiment analysis of incoming/outgoing calls, calendar information). The individual correlation of a sensor with perceived stress and its ability to contribute to stress detection in a portfolio of sensors is a question for subsequent empirical evaluation. We do not hypothesize and evaluate a causal relationship between sensors and stressors or strains from the stress model, but aim on stress prediction.

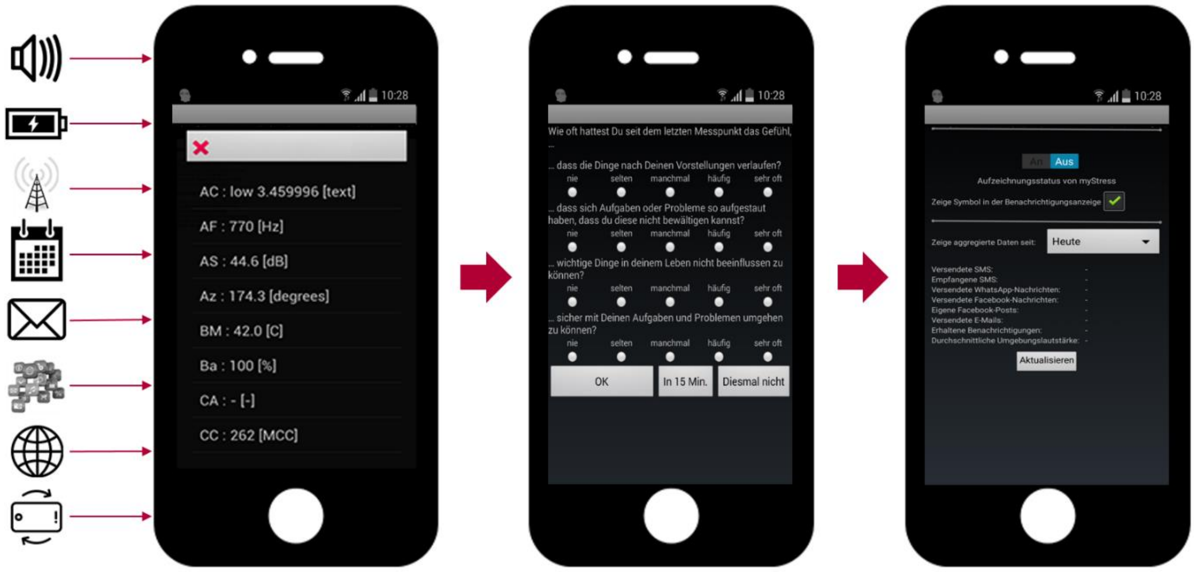


Figure 15: Screenshots of the Application

The implemented sensors can be divided into two categories. Sensors of the first category probe at a defined time interval, e.g., the ambient temperature, audio frequency, and illumination sensors. A high probing frequency of only few seconds in the alpha version lead to very high battery consumption and low battery life of the testers' smartphones. Feedback included that a minimum battery life of 24 hours given normal smartphone use would be desirable. As a trade-off between granularity of measurement and resource efficiency, we set the probing interval to 5 minutes in the final version of the prototype. Sensors of the second category respond to specific events, e.g., incoming or outgoing text messages, the pressing of the power button, or notifications. Event sensors can count the number of occurrences, identify state changes, or store additional information like the sentiment of an outgoing text message or the duration of a phone call. In the alpha release, extended data such as the full message text or the caller ID was stored, but reduced due to severe privacy concerns. Table 15 features the full list of sensors that reference at least one stressor or strain from the stress model. The resulting list features many physical and psychological stressors as well as behavioral strains. References to physical and cognitive strains (e.g., reduced typing accuracy) are present but rarer. However, mobile sensors can cover not all aspects of the stress model, as a holistic stress assessment requires contextual data (e.g., information on the workplace), explicit user input (e.g., on emotions), or physiological measurements (e.g., sweating).

In order to assess the relationship between sensors and perceived stress, the prototype asks the user three times a day (at morning, midday, and evening) to answer a short stress questionnaire on their smartphone. While this questionnaire is not unobtrusive, it is only included for researching how to assess stress unobtrusively – we aim to make it redundant and spare it within the final DTM. The questionnaire consists of the 4-item Perceived Stress Scale (PSS-4) proposed by Cohen et al. (1983), which is one of the most frequently used scales to assess perceived stress. It uses four items on a 5-point Likert scale ranging from 0 to 4 to measure the individual's stress perception based on stress-inducing aspects of life (unpredictability, uncontrollability, and over-load). The questions are phrased in natural language and, hence, independent of content and population. The final score calculates as the sum across all 4 items, whereby two items are re-versed.

The PSS was shown to be a valid measure for linguistically quantifying stress sensed by a human being and is frequently used in research (Haushofer and Fehr 2014; Heidt et al. 2014; Hobfoll 1989). Unless the fact that PSS cannot be used as a diagnostic instrument, it is suitable to perform comparisons (Cohen 2010). Although the PSS-4 has lower internal reliability than the longer 14-item version (PSS-14), it provides much more usability for measuring perceived stress over spatial distance (Cohen et al. 1983). In this trade-off between internal reliability and usability, we chose usability to be an important aspect for the present study. We try to eliminate the questionnaire as a confounding variable to reduce bias. The original questionnaire design by Cohen et al. (1983) enquires how often participants felt a certain way in a specific period (originally one month). Although the classic version of PSS-4 uses one month, it remains valid on significantly smaller periods (Cohen 2010). Thus, we changed the original PSS-4 wording "In the last month, how often have you felt […]" to "Since the last survey […]" for all four items: 1) "[…] that you were unable to control the important things in your life?", 2) "[…] confident about your ability to handle your personal problems?", 3) "[…] that things were going your way?", and 4) "[…] difficulties were piling up so high that you could not overcome them?". The scores of items 2 and 3 are inverted for summation.

To maintain general data privacy and to adhere with the Code of Conduct (European Commission 2015), the user has to manually activate data collection after installation and can pause it at any time. The prototype uploads the data twice a day to a cloud storage. This interval reflects a trade-off between data timeliness and resource consumption. In order to spare the user's limited data connection, the upload only occurs with an existing Wi-Fi connection. On the resulting data set, we explore associations of sensors and perceived stress using regression and classification models.

Evaluation

In this subsection, we evaluate the generality, ease of use, effectiveness, and operationality (Sonnenberg and Vom Brocke 2012) of the proposed DTM for life-integrated assessment of stress based on the Framework for Evaluation in Design Science Research (Venable et al. 2016) with consideration of the requirements. Following Venable et al. (2012) and Sonnenberg and Vom Brocke (2012), this evaluation serves three purposes: (1) Evaluate the prototype formatively while under development, (2) evaluate the effectiveness and ease of use of the prototype for the mobile sensing of stress-related factors, and (3) evaluate the operationality and generality of model building for stress assessment upon the unobtrusively gathered data.

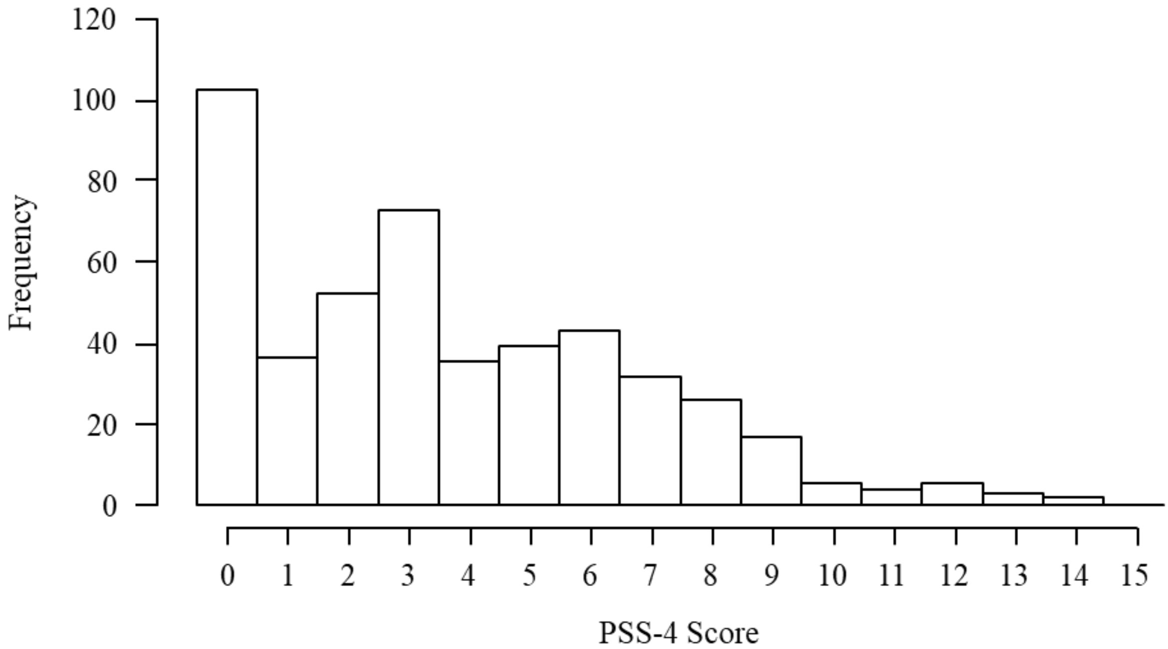
The presented DTM – a prototypical mobile DTM for life-integrated assessment of an individual's perceived stress – can be considered a socio-technological process artifact (Venable et al. 2012) demonstrating the assessment of human stress based on smartphone data. We evaluate the DTM using design science and prototyping evaluation methods (Hevner et al. 2004; Peffers et al. 2012) and perform five consecutive evaluation episodes (Venable et al. 2016): 1) Literature-backed design and ex-ante validation of sensors' relevance and theoretical utility, 2) agile development of the prototype including alpha and beta testing to ensure ease of use, 3) examination of operationality and generality of life-integrated sensing in the field study, 4) data analysis and model building of a general stress assessment model including performance tests for determining its effectiveness, and 5) operationality and performance of model personalization. A further episode which comprises ex-post evaluation activities similar to Eval4 (Sonnenberg and Vom Brocke 2012) should test DTM's applicability to advanced application scenarios such as stress-sensitive adaptive enterprise DTMs. This is yet up to future research.

Episode 1 – Literature-backed Design: In the subsection Theoretical Background, we elaborated a schematic concept for mobile stress assessment supported by literature on stress and mobile sensing as a first review of formative knowledge, which the application and its sensors are based on.

Episode 2 – Agile Development: The subsection Prototypical Instantiation describes insights into critical success factors we gained during agile prototyping. In first versions of the prototype, alpha and beta testers expressed severe security and privacy concerns; these were addressed by transparently communicating what the system does and does not measure. The prototype also suffered from inefficient resource use; this was corrected by eliminating power-consuming defects and reducing sensor-probing frequency.

Episode 3 – Public Field Study: We apply the prototype within a field study to evaluate its acceptance among users and determine the general operationality of life-integrated mobile stress assessment. To reach a broad and diverse audience, we published the prototype in the Google Play Store and recruited participants in social media, particularly via Facebook, Twitter, and Quantified Self forums. The app was installed on 222 devices (96 from Germany, 50 from the US, 19 from India, and 13 from Brazil) and 137 different smartphone models with Android versions ranging from 2.3.3 to 5.0.1. However, during the four months of data collection, only 40 users provided an informative dataset of sensor data in combination with at least one answered stress questionnaire in total. Several factors might have contributed to the discrepancy between installations and data provision: a non-existing Wi-Fi connection could have impeded data up-load, data privacy concerns could have prevented the user from activating data collection, or users could have installed the application out of curiosity without the actual intention to support our research. In addition, there was no incentive for participation. Instead, we relied on the users' motivation to support research and to potentially benefit from a more mature system in the future. Anecdotal evidence suggests that the strongest reason for not participating is the lack of perceived usefulness, as the prototype only gathers data, but does not yet provide feedback or intervention recommendations. We plan to address this in future versions.

The 40 participants, who uploaded at least one questionnaire, answered the questionnaire 474 times in total (an average of 11.5 questionnaire reports per user). The following data analysis is restricted to these 40 users, as the ability to build a statistical model for stress assessment hinges on the availability of questionnaire data, even if this data is not part of the final system. The overall distribution of PSS-4 scores in our user base (Figure 16) aligns with representative surveys on the distribution of stress (Cohen and Williamson 1988; Statista 2010; Warttig et al. 2013). Although this shows a clear trend towards low levels of perceived stress, we observed differences in stress intensity over time and between users.



Note: values for the PSS-4 scale ranging from 0 (no stress) to 16 (high stress); n = 474

Figure 16: Distribution of Perceived Stress

Since we did not incentivize participation in the field study, the general interest and enduring commitment of participants during the field study suggests that users are open to the idea of life-integrated stress sensing. The successful deployment and data collection of the prototype in the field study substantiate the operationality of life-integrated sensing. A caveat is the high rate of non-users, presumably because the prototype did not provide any benefit or valuable feedback to users.

Episode 4 – Data Analysis and Model Building: We evaluate the prototype's effectiveness by using the data gathered within the field study to create a universal (i.e., person-independent) model for the assessment of perceived stress. For analysis, we link each stress level observation with recent sensor data and test regression and classification performance. Pre-processing presumes that the analysis of linear relationships might not be sufficient and, thus, extends the number of features by performing various transformations on the raw data. In this course, we logarithmize the data, independently apply a median split, and include the untransformed data. The same transformations are performed on a copy of the raw data, in which outliers, i.e., sensor values that are not within the interval of 1.5 interquartile ranges from the lower and upper quartile of each sensor, are censored. As outliers might be a valuable indicator for exceptionalities causing stress, we do not fully remove them. For feature creation, we aggregate all data between two stress level observations, calculate the minimum, maximum, range, median and mean for numerical data, and count occurrences in absolute numbers and normalized to one hour for categorical and event data. Time features for the daytime (morning, midday, evening) complete the feature list. In case of missing values, we assume normality and replace them with the variable's median.

This pre-processed data provides the foundation for training a regression model that predicts stress levels on the PSS-4 scale (ranging from 0 to 16). Standard linear regressions (ordinary least squares, panel, or stepwise regressions) are not applicable, because the data presents the problem of high dimensionality with a substantially larger number of variables than observations) and, thus, harbor the danger of overfitting. Instead, we use three linear methods suitable for high-dimensional regression problems (Hastie et al. 2005), elastic net regression and its two special forms ridge and lasso regression. As model sparsity is an important issue in mobile processing, we evaluate model performance in predicting the level of perceived stress based on the adjusted R^2 in cross-validation (Alpaydin 2004). Although the elastic net produces less prediction error, we find that the best model selected according to adjusted R^2 is based on lasso regression fitting. It explains 41 % of the variance in users' perceived stress, uses 94 variables from 21 of the 38 sensors in total (Table 15), and achieves an adjusted R^2 of 0.26 with a RMSE of 2.69 and a mean absolute error (MAE) of 2.12 on the 0 to 16 scale.

To check the robustness of the results, we test if users with a low number of observations (e.g., those supplying questionnaire data only once) could falsify the regression model. Thus, we additionally analyze the subsets of users with at least 10 or at least 20 stress level observations. The best model for users with 10 or more observations achieves an in-sample cross-validation RMSE of 2.46 and generalizes with an RMSE of 2.69 when applied on the dataset of all users including those with fewer observations. The result further improves for 20 or more observations with an in-sample RMSE of 2.11; however, an evaluation against all users returns an RMSE of 3.03. Not surprisingly, fit statistics improve when reducing the dataset, as the model can better approximate a smaller number of users. Another interesting discovery is that the RMSE from validating against all users is minimally affected, irrespective of whether training is performed with data from all users or data from users with at least 10 observations. This suggests that no overfitting problem exists with the best regression model.

As a further robustness check, we additionally train a classification model, which aims to distinguish the two categories ‘no stress’, which denotes PSS-4 scores from 0 to 3, and ‘stress’, which represents the scores 4 and above. We set the boundary at 4, because this score implies that in average each item of the PSS-4 scale has been answered with a value of 1, which we assume to be a reasonable and legitimate minimum condition for the ‘stress’ category. While all three binary classification models we trained – a boosted decision tree (BDT), a decision forest (DF), and a support vector machine (SVM) – achieve good overall performance in a ten-fold cross validation setting, the BDT performs best. It predicts the correct category with an accuracy of 81 % (DF 80 %, SVM 75 %), and achieves a precision of 78 % (DF 77 %, SVM 72 %) and a recall of 80 % (DF 79 %, SVM 72 %) for predicting the presence of stress with an area under the ROC curve (AUC) value of 0.86 (DF 0.85, SVM 0.82).

Episode 5 – Model Personalization: The performance of the models trained with data from users with at least 10 or 20 observations suggests that targeted models for individuals or small user groups may outperform a universal model for in-sample stress assessment. To verify this, we perform first personalization performance tests. For each of the 17 users that provided at least 10 stress observations, we built a lasso regression model on a dataset, in which the test user’s data is excluded. A stochastic gradient descent with adaptive learning rate (Zeiler 2012) continually learns each observation and updates the model parameters iteratively. For 14 users, this personalization resulted in significantly better error metrics (measured by a reduction of the mean squared error by at least 20 %). The three users, where this improvement has not been achieved, had already good error metrics with the universal model. An extensive analysis of how personalization improves stress assessment is subject to future research.

Sensor	**Description and unit of measurement**	**Model**
Connectivity		
Cell Identifier	Identifier of the current cellular network [nominal]	no
Location Area Code	Location area code of the current cellular network [nominal]	no
Network Code	Network code of the current cellular network [nominal]	no
Data Connection Status	Is the device currently connected to cellular data [binary]	yes
Roaming Status	Is device currently roaming [binary]	no
Wi-Fi Connection Status	Is device currently connected to a wireless network [binary]	yes
Battery		
Battery Charging Status	Is device currently charging [binary]	no
Battery Level	Current battery level [%]	yes
Battery Temperature	Current temperature of the battery [°C]	yes
Mobility & Activity		
Orientation	The device’s current azimuth, pitch, and roll [3x degrees]	yes
Activity	Variance of device’s orientation and its interpretation [none/low/high]	yes
Step Counter	Changes on device’s pedometer within the poll interval [steps]	no
Communication		
Calendar Events	Number of calendar events within 24 hours [count]	no
Call Log	Number [count], duration [min] and type [in/out] of phone calls	yes
Incoming Text*	App-specific notification about incoming messages [event]	yes
Outgoing Text*	App-specific notification about outgoing messages [event]	yes
Text Length*	Length of outgoing messages [characters]	no
Text Sentiment*	Sentiment of outgoing messages [positive/neutral/negative]	no
Typing Speed*	Typing speed of outgoing messages [characters per min]	yes
Typing Accuracy	Number of deleted characters [count]	no
Smartphone Usage		
RAM Available	Currently available memory (RAM) [KB]	no
Running Apps	Number of currently running apps (multiple possible) [count]	yes
Visible Apps	Number of currently visible apps (multiple possible) [count]	yes
Screen Switching	Indicates that user switched screen over [event]	no

Sensor	Description and unit of measurement	Model
Environment		
Ambient Light	Brightness of current ambient light [Lux]	yes
Ambient Audio	Amplitude [dB] and frequency [Hertz] of current ambient sound	yes
Ambient Temperature+	Temperature of the smartphone's environment [°C]	no
Ambient Humidity+	Humidity of the smartphone's environment [%]	no
Ambient Pressure+	Atmospheric pressure in the smartphone's environment [bar]	yes
Proximity+	Distance of the smartphone to the next object [meter]	no
Location	Latitude [degree] and longitude [degree] of the current location	no
Location Changes	Frequency of minor location changes [count]	yes
Weather: Temperature	Temperature at the current location [°C and °F]	yes
Weather: Humidity	Humidity at the current location [%]	no
Weather: Wind	Wind speed at the current location [miles per h]	yes
Voice		
Voice Energy	Energy of voice signal using L1-, L2- and Linf-norms [ordinal]	yes
Voice Spectral Density	Power spectral density of 50, 250, 500 and 1000Hz [ordinal]	yes
Voice Frequency	Frequency spectrum using 12 MFC coefficients [ordinal]	yes

Notes: '*' currently supports SMS, WhatsApp, Facebook Messenger and mail apps; '+' only available on some devices

Table 15: List of Sensors in the Prototype and their Relevance for the Best Model

Discussion

We designed and developed a DTM for life-integrated stress assessment with consideration of both psychological literature on stress and comparable scientific efforts on the sensing of psychological phenomena. As described in the subsection Prototype, the prototype fulfills all design requirements: Data was gathered continuously in a life-integrated way with adherence to important non-functional requirements. The PSS-4 surveys were only used for validation; they are not part of the design itself. The achievement of reasonable performance in assessing perceived stress levels shows the general feasibility of life-integrated stress assessment via smartphone. The best regression model, which was selected by the criterion of minimum adjusted R^2, predicts PSS-4 scores on a scale ranging from 0 to 16 with an average accuracy (MAE) of +/-2. There are no guidelines or benchmarks specifying acceptable performance for this type of system in an uncontrolled environment and we do not claim that our method of statistical analysis is optimal. However, we do claim that explaining 41 % of the variance in perceived stress is substantial for a DTM, which does not at all require user cooperation in daily use.

During agile prototyping, we gained various important insights into critical success factors of life-integrated stress assessment DTMs. In their combination, these learnings help with details on the design of life-integrated stress assessment and might help researchers and practitioners likewise to build better DTMs. Most importantly, the accessibility of stress assessment is vital for its use and acceptance. Obtrusiveness, that is, the necessity of attention or interaction with the user, puts up high barriers for broad application. Our research shows that life-integrated stress assessment is feasible and a valuable approach to stress assessment. But it also shows that excessive resource consumption, in terms of data storage or upload, battery consumption, or processing power, might already be partially obtrusive as it brings the system's existence into the user's attention. Another very important facet is, for example, to consider the protection of the user's privacy. For some people the stress level itself is highly sensitive information. This holds especially true, when the information is shared with others, e.g., with the employee's supervisor in organizational stress management applications. Privacy is even more important with the full set of sensor data that allows for the creation of movement, usage and behavior profiles. Consequently, applications should establish appropriate privacy protection mechanisms that prevent external access to sensitive information on a need-to-know basis (Sutanto et al., 2013). One potential measure could be to fully renounce an internet-based data upload and perform computations fully on the user's device. As a third learning, user feedback suggests that they are significantly more tolerant towards limited privacy and resource saving, if the DTM provides a clear benefit to the user.

The manifold application scenarios target several stakeholder groups for the concept of life-integrated stress assessment range from pure information provision to detailed feedback or the automation of stress-reducing routines. The most obvious scenario is the immediate use to support the individual user. Stress assessment can be directly used to support the user's stress management by providing feedback on the current stress level. Mobile apps for personalized and sentiment-dependent recommendations can use the stress level to recognize the individual's need for relaxation. The recently suggested design of stress-sensitive adaptive enterprise DTMs (Adam et al. 2017) can be operationalized building on the presented life-integrated, continuous stress assessment and help business and users likewise. Stress-related lack of concentration in hazardous work scenarios such as the interaction with robots or machines can be tackled with countermeasures for the benefit of the human's safety. Similar purposes are imaginable for the support of business-critical decisions: a stock exchange app, for example, can take the increased risk propensity of the stressed individual into account and warn them of risky trades in advance. Furthermore, personalized stress-aware design and adaptation of user interfaces can help improve customer experience. These examples illustrate the broad range of application scenarios that emerge from the possibility to unobtrusively evaluate the stress level of individuals whenever and wherever required.

Conclusion

In this section, we presented a DTM targeting the life-integrated and continuous smartphone-based assessment of perceived stress. We followed the design science research methodology of Peffers et al. (2007) and elaborated the DTM in several steps. Based on problem relevance, theoretical background, and design requirements, an exemplary implementation for the Android platform has been developed. This prototype helped to demonstrate the general operationality of life-integrated mobile sensing and its applicability for the assessment of perceived stress. A binary classifier demonstrates its value for determining stressed and non-stressed mental states. The universal stress assessment regression model elaborated in this work links data from smartphone sensors to their application for stress valuation and confirms the feasibility of life-integrated and continuous stress assessment. This model is based on data gathered within a public field study, in which 40 users provided data by using the prototype. Therefore, the presented method enables the development of systems that apply a life-integrated and continuous assessment of perceived stress as input for adaptation mechanisms that provide targeted technological or manual stress management interventions. Furthermore, the method can be used as an indicator for the user’s current affective state to provide relevant information to user adaptive systems enabling a more intuitive interaction (Morana et al. 2017).

Some aspects of the present study call for subsequent research to further test and extend our results. First, stress is a multi-faceted phenomenon. We targeted perceived stress, which is not necessarily identical to actual stress (Riedl 2013). Thus, going beyond perception towards physiological measurements will be a valuable addition to the present research. Second, our system relies on the regular usage of one primary smartphone. The exact boundaries of the scope are not yet clear. Future field tests should measure the intensity of smartphone usage, and recruit participants with diverse intensities to explore how intense smartphone interaction must be for reliable stress assessment. Third, it is by no means clear that a technological solution for perceived stress assessment is the most appropriate solution because smartphones themselves are potential stressors (Lee et al. 2014). Nevertheless, we contend that it is worth exploring and evaluating how smartphone-based sensing can foster the development of innovative technologies that appropriately interact with the stressed or chilled individual. Fourth, the results of the study should be confirmed on a larger dataset that features more participants and a longer evaluation period. Fifth, an evaluation involving the actual use of stress assessment in a realistic application context should be conducted. Sixth, refined statistical models or aggregation may improve model performance. For example, future research could investigate what amount of historical sensor data is best to predict stress. Moreover, the value of personalized models is worth exploring. For new users, stress assessment could initially be based on a pre-trained general model as presented in this section; the model could then be improved over time through personalization, similar to the approach of Rachuri et al. (2010) use for personalized emotion detection. Finally, future work should link stress assessment with stress management interventions. A first step might be providing feedback to users. From a wider perspective, unobtrusive and continuous assessment of perceived stress can be the foundation for stress-adaptive information and enterprise systems, as suggested by Picard and Liu (2007) and Adam et al. (2014, 2017).

5.3.Deriving a Design Theory for Mobile Stress Assessment

The mobile prototype for life-integrated stress assessment presented in the previous section has demonstrated the feasibility of assessing the user's psychological state from data collected by sensors. However, in the course of the research activity, some obstacles and challenges have been identified that make a reliable design of a mobile stress assessment system difficult, which would be a necessary prerequisite for a technical component to be adapted to the social component. Accordingly, the following section investigates how a mobile stress assessment should look like.

Digitalization affects all domains of life, including our work and private lives. Emerging digital technologies will increasingly permeate our lives leading to new ways of working and living. Prominent examples include the feasibility of autonomous driving, living in smart homes, using advanced work assistance systems, and the wide rollout of digital healthcare services (Maedche et al. 2016). While this digitalization of everything brings many advantages at the individual, organizational, and societal levels, it also has severe downsides (Gimpel and Schmied 2019). For example, these manifest in reports of employees’ increasing workload, blurring boundaries between work and private life, and a higher prevalence of technology-related stress, all of which contribute to an overall increase of individuals' stress. Conversely, the individual resources available to deal with stress do not rise to the same extent, potentially deteriorating personal well-being (Riedl 2013) and causing severe illnesses such as burnout or depression (Bacharach et al. 1991; Hammen 2005). Besides the individual adverse consequences, excessive stress potentially also impacts the economy and society due to sick leave (Moreau et al. 2004), bad decision making (Astor et al. 2013), and rising healthcare costs (Varvogli and Darviri 2011).

Although digitalization evidentially amplifies this trend, the widespread availability of mobile devices like smartphones or wearables can also deliver a solution and positively contribute to stress management. Already today, first information systems (IS) assess and report the user's stress level to support them in stress management. In the future, IS might adapt their workflow according to the user's stress or affective state and assist them in coping with the situation. Over the last decade, various publications have called for the development of neuro-adaptive information systems, systems that recognize the neurophysiological state of the user and positively adapt to it (Riedl 2012; Vom Brocke et al. 2013). First publications responded to this call by proposing a simple design blueprint for stress-sensitive adaptive enterprise systems (Adam et al. 2017) or ambulatory stress prevention (Friemel et al. 2018; Jimenez and Bregenzer 2018).

An important prerequisite for building effective stress management assistance is the assessment of individuals' stress. Various approaches for stress assessment exist: Established questionnaires like the Perceived Stress Scale (Cohen et al. 1983) can question individuals about the stress they perceive. Physiological measurements such as skin conductance (Riedl 2013) or cortisol levels (Riedl 2012) can help determine stress from a biological perspective. Mobile devices' wide sensing capabilities enable another approach: the data-based assessment of stress using data on the user, their environment, and the interaction between the two. In contrast to the pure perception- or biology-based views, mobile stress assessment (MSA) does not necessarily measure a concept directly linked with stress. However, it uses data analytics methods to relate mobile acquired sensor data with stress in either a user-independent or a personalized way. Various instantiations have already demonstrated MSA's feasibility for different applications (Gimpel et al. 2015, 2019b; Lane et al. 2011; Lu et al. 2012; Wang et al. 2014). Although the design of these systems has a lot in common, for example, regarding their architecture, researchers designing MSA systems rarely build on insights collected and reported by other MSA scholars. General guidelines with aggregated knowledge on how to design MSA systems are yet missing. However, such guidelines would help researchers and practitioners successfully develop MSA systems and might significantly increase MSA systems' quality. Therefore, we argue that a design theory for MSA that guides MSA designers from research and practice in developing an MSA instantiation specifically for their intended application would be valuable for further application and theory development and can foster the future development of information systems targeting stress management. Therefore, we elaborate on the following design objective:

DO) Compose a design theory for mobile systems capable of assessing users' stress for all intended applications of MSA.

We follow standard design science research (DSR) methodology (Hevner et al. 2004; Peffers et al. 2007) to develop a design theory (Gregor 2006; Gregor and Hevner 2013; Jones and Gregor 2007) for MSA. For this purpose, we extensively analyze the existing literature on MSA, consolidate extant design knowledge dispersed across 136 MSA studies, and produce new design knowledge by implementing the theoretically elicited design within five own MSA prototypes. By building our design theory on extant design knowledge, our research addresses a major shortcoming of current DSR practice manifesting in the limited reuse of existing design knowledge (Vom Brocke et al. 2020). Combining old and new design knowledge, we compose the design theory from several interrelated elements: a set of *design requirements* for MSA, an *abstract blueprint* proposing a common architecture, *design principles* guiding the design, *design features* detailing the implementation of the blueprint and principles, and *trade-offs* that need to be made when implementing a specific MSA system. These elements and the design theory presented here contribute to the literature on the topic of MSA by providing researchers and practitioners with extensive design knowledge on how to develop effective MSA systems. Complementary, it contributes to DSR literature by providing an example of a theoretically grounded and empirically enhanced design theory that can inspire further researchers to strive for consolidated design knowledge and thereby facilitate effective IS development. While we tested the design with five MSA prototypes, it has not yet been subject to a long-term evaluation by different research parties. Future research may build on this design theory by giving further evidence for its effectiveness in producing IS that prevent the adverse psychological, physiological, and behavioral consequences of excessive stress.

We employ a structure similar to the publication schema for DSR suggested by Gregor and Hevner (2013). Next, we shed light on the theoretical background on stress theory and mobile stress assessment and derive six design requirements. Subsequently, we describe the employed research process. After that, we describe design knowledge relevant to MSA's design, which we obtained from our extensive literature analysis. Building n this, we identify archetypes of MSA systems in literature based on cluster analysis results. We then report insights from our prototyping activities onto what needs to be considered when tailoring MSA to their specific intended application. Finally, we combine the results from literature and cluster analysis and the prototyping activities and compose a design theory, emphasizes the theoretical and practical value of our research and conclude with a description of the current work's limitations as well as an outlook on ongoing and future research.

Theoretical Foundation

Justificatory knowledge related to the design objective originates from research on stress theory and mobile stress assessment. Stress is the targeted area of application. Mobile stress assessment literature provides the fundament for condensing knowledge on the design of human-centered information systems in general and MSA in particular.

Mobile Stress Assessment

With the increasing ubiquity of information technology, information systems play a growing role in supporting and assisting the user (Maedche et al. 2016). Researchers have understood this need for user centricity in information systems. Recent IS literature suggests first solutions for ambulatory stress prevention (Adam et al. 2017; Friemel et al. 2018; Jimenez and Bregenzer 2018). However, the development of such systems is not trivial and requires the continuous and reliable assessment of stress. To do so, assessment systems need to "minimize retrospective biases while gathering ecologically valid data, including self-reports, physiological or biological data, and observed behavior, e.g., from daily life experiences" (Trull and Ebner-Priemer 2013, p. 1), e.g., by means of mobile hardware. Stress assessment, and MSA in particular, has recently received significant attention due to its potential and complexity. In this, MSA refers to a class of mobile information systems that use sensor data on the user (e.g., physiological data), their environment (e.g., environmental conditions), and the user-environment-interaction (e.g., behavioral data) in order to determine the user's stress state for various intended applications (e.g., measuring individual daily stress, mitigating dangers of stress at the workplace).

Several literature reviews on the topic have been published over the last years, which aggregate the current state of the art of identifying stress or stress-related concepts using mobile data: Þórarinsdóttir et al. (2017) published a comprehensive review of the literature on smartphone-based stress assessment. Aigrain (2016) analyzed the topic of stress and discusses different strategies for detecting stress in various settings. Greene et al. (2016) published a survey on affective computing for stress detection. Habib ur Rehman et al. (2015) further analyzed the capability of mining personal data acquired by smartphones and wearable devices. Glenn and Monteith (2014) researched medical and commercial projects on pervasive healthcare enabling remote disease monitoring including stress.

We found that several researchers have already exploited mobile data for recognizing human psychological conditions in various ways: (1) assess stress via only a smartphone, (2) assess stress with several different devices (e.g., two smartphones or a smartphone plus an additional device such as a wearable), and (3) recognize not stress but emotions, mood, or activity (e.g., walking, running, cycling) with similar measurement techniques. The following paragraphs address these categories sequentially.

Research assessing stress using a single smartphone is rare. BeWell (Lane et al. 2011) and StudentLife (Wang et al. 2014) originating from the same research institution are Android applications that assess the smartphone user's stress level by tracking activities which affect physical, social, and mental well-being. The relevant data is collected by continuously reading multiple smartphone sensors including the microphone, accelerometer, and light sensors. BeWell extends this data by integrating additional user information entered through a web portal. StudentLife pushes multiple questionnaires to the smartphone which must be answered by the user and extends the collected data using location-based information within the research institution's facilities (e.g., the traveled distance inside buildings based on Wi-Fi logs). However, both applications require the user to answer multiple (an average of eight) questionnaires daily, which serve as an additional data point and are not only used for model training purposes. This makes these systems rather obtrusive. Bauer and Lukowicz (2012) identify longer stressful periods, e.g., exam weeks, from smartphone usage but do not directly assess stress.

Several applications assess stress with a smartphone plus one or more additional devices. While both Ferreira et al. (2009) and Kocielnik et al. (2013) use external devices to measure body reactions (e.g., increased sweating, rapid heartbeats), Sano and Picard (2013) attempt to recognize stress with mobile sensors, a wrist sensor, and several daily questionnaires. Equally important, Lu et al. (2012) measure stress by analyzing the human voice and use a second phone to distinguish between speakers.

Artifacts related to but not directly performing stress assessment include emotion, mood, and activity detection systems. Most technical systems aiming to assess these conditions use exclusively smartphone data. The only exception is Choudhury et al. (2008), who use an external device to measure additional parameters (e.g., humidity). This data can be enriched with additional user input (Chang et al. 2011; LiKamWa et al. 2013) or gathered unobtrusively (Albu et al. 2008; Rachuri et al. 2010).

In general, different research projects have shown the feasibility of basing assessments of stress or stress-related psychological factors on the human voice (Chang et al. 2011; Lee et al. 2012), sleep (Lane et al. 2011; Sano and Picard 2013; Wang et al. 2014), social interaction (Bauer and Lukowicz 2012; Wang et al. 2014), location information (Lee et al. 2012; Rachuri et al. 2010), ambient information (Lee et al. 2012), body reactions (Kocielnik et al. 2013), activity recognition (Choudhury et al. 2008), and behavioral patterns (Ferreira et al. 2009; Kocielnik et al. 2013; Lee et al. 2012; LiKamWa et al. 2013). Furthermore, several artifacts aim at unobtrusively sensing different parameters in a mobile setting (Lee et al. 2012; Rachuri et al. 2010) to obtain less biased data (Lee et al. 2014). Various systems also aim for the continuous sensing and assessment of the user's mental state (Lee et al. 2012; Rachuri et al. 2010), especially for emotion, mood, and activity detection (Ferreira et al. 2009; Kocielnik et al. 2013; Lee et al. 2012; LiKamWa et al. 2013).

Most of the systems presented in the previous paragraphs target the assessment of everyday stress or stress from certain groups of people (e.g., students' exam stress). However, we also identified some MSA instantiations that target very specific use cases. Sandulescu and Dobrescu (2015) describe the development and use of a wearable shirt to detect stress experienced by firefighters in actions. This system aims to proactively warn mission supervisors about high stress levels of one or more persons in their action force to prevent potential dangers for their people and their mission. Other studies suggest the use of wearable gloves to measure a driver's stress indicated by steering wheel movements (Lee et al. 2016; Lee and Chung 2017). Similarly, Rodrigues et al. (2015) aimed to systematically identify location-based stressors for public bus drivers. Although these application purposes of MSA are rather exotic, they show the broad bandwidth and high potential of MSA. Thus, our design theory aims to hold for all MSA systems independently of their intended application.

Design Requirements

All examples of MSA systems described in the previous section have in common that they share the same set of high-level design requirements. These design requirements refer to important properties of an MSA system and specify such systems' purpose and scope. We derive the design requirements from exemplary literature on MSA and its design objective to establish the common goals of MSA for different intended applications. Three design requirements refer to the MSA systems' functional system behavior (DR1-3) and three design requirements describe system quality requirements (DR4-6).

As with every diagnostic procedure, the availability of valid data is an essential prerequisite. Particularly external validity is required to ensure whether observed associations can be generalized from the sample to the context (Bhattacherjee 2012, p. 36) in the sense of stress assessment. Due to the different causes and manifestations of stress, MSA typically considers data from various sources. Therefore, an MSA needs to **gather valid data on the user and their environment** (DR1). Data on the user includes physiological data, behavioral data, or data from introspection (Ayzenberg et al. 2012; Gimpel et al. 2015; Wang et al. 2014). Data on the environment is required to capture external stimuli responsible for causing stress in the users of an MSA system. This environmental data may include, for example, ambient volume, ambient light, temperature, humidity, or air pressure (Mayya et al. 2015). If gathered rigorously, data from both sources provide a sound foundation for stress assessment.

With valid data being a prerequisite, another crucial MSA property is the **reliability of the calculated stress levels** (DR2). Thus, MSA needs to employ consistent methods to determine the stress levels based on valid measurement data. However, there is no one-fits-all solution. Instead, the determination of stress needs to be adapted to the MSA system's specific intended application, for example, regarding the granularity of the reported stress level or the individuality of the stress model (Garcia-Ceja et al. 2016). Thus, this requirement needs to be thoroughly considered in designing various aspects of the MSA system.

Given reliably determined stress levels based on valid data, the system typically needs to **report the results to a defined recipient understandably and transparently** (DR3) to avoid misunderstandings. The specific shape of the reporting depends, just like the calculation of stress levels (DR2), on the intended application of the MSA system. To report a binary classification result (i.e., stress, no stress), other means may be suitable for interval-scaled stress scores. For example, binary stress values of public bus drivers can be visualized on a city map to identify potential areas of risk (Rodrigues et al. 2015). A second example shows that a smartphone-based MSA system can visualize an individual's interval-scaled stress score using an app-based graphical user interface (Mayya et al. 2015). The key to transparently reporting stress levels in MSA is to ensure that the results can be used comprehensively and goal-oriented for the defined recipient and the intended application.

In addition to the three functional design requirements that describe the key steps of an MSA system (DR1-3), we have identified three important quality requirements for such systems. The first quality requirement demands MSA systems to be designed in a resource-saving way, **keeping the system's technical resource consumption at an appropriate level** (DR4). In this context, resources refer to technical resources, such as the amount of data, storage capacity, computing time, or electric power. The reason for the required resource efficiency is due to the mobility of MSA systems. Suppose an MSA system is designed as a standalone application on a mobile device. In that case, high amounts of data may lead to bottlenecks in computing power or storage capacity as these resources are limited on mobile devices. When a system adopts a client-server architecture to overcome this issue, there might be a bottleneck in data throughput between client and server. Regardless of the system architecture, the sensors used to require additional energy on the main device. Finally, the specific intended application of the MSA system determines which of these resources must be kept at a modest level and which can be utilized more intensively.

Of course, the results of an MSA system and the **algorithms used must be accurate** (DR5). The prerequisite for algorithm accuracy is valid measurement data (DR1) and the outcome are reliable results (DR2). Much of the literature on MSA uses machine learning techniques such as Naïve Bayes classifiers, random forests (Garcia-Ceja et al. 2016), support-vector machines (Sandulescu and Dobrescu 2015), or convolutional neural networks (Cho et al. 2017) to detect stress from gathered data. Depending on the data quality, the stress model employed (i.e., general or personal), or the specific algorithms used, achievable accuracies may vary. How accurate an algorithm must depend on the use case. For example, an MSA system used for medical stress diagnosis must provide more accurate results than a system assisting users in improving their everyday well-being. A system providing a continuous stress score must have greater accuracy than one that binarily distinguishes between stress and no stress. Overall, algorithm accuracy is an important quality criterion for MSA systems. However, it cannot be determined generally.

Finally, it is important to mention that MSA systems must always interact close to the user's environment in order to be able to collect data about the user and their environment accordingly. Hence, MSA systems should **provide a high level of user acceptance** (DR6).

All the presented design requirements are prerequisites for an MSA system to achieve this acceptance. DR1, DR2, and DR3 describe the essential functions of an MSA system. A system not meeting this functionality will not be accepted by users. Further, adequate consumption of technical resources (DR4) and the accuracy of the used algorithms (DR5) affect user acceptance (Gimpel et al. 2019a). Besides the explicitly defined design requirements, user acceptance is subject to further requirements such as privacy and unobtrusiveness. As some MSA systems capture sensitive user data such as physiological data (Mayya et al. 2015; Rodrigues et al. 2015), behavioral data, or personality traits (Bogomolov et al. 2014), ensuring a high level of privacy is essential to achieve user acceptance. Meulendijk et al. (2014) list privacy as a separate design dimension in their list of non-functional requirements for mobile apps in the context of health. Also, unobtrusiveness is an essential prerequisite of MSA systems, as potential users will not accept a system that bothers or obstructs them. In contrast to the previously presented design requirements, user acceptance is not fundamentally dependent on the use case but should always be kept on a high level.

Research Process

Our DSR project addresses the objective of elaborating a design theory for MSA systems. It employs the design science research methodology by Peffers et al. (2007) and integrates evaluation activities iteratively into the research process (Figure 17) following Venable et al. (2016) and Sonnenberg and Vom Brocke (2012). Of the four evaluation strategies proposed by Venable et al. (2016), we select the Human Risk & Effectiveness strategy because the MSA design theory needs to prove its effectiveness for producing MSA systems that assess the user’s stress in realistic scenarios.

Methodology

We build on common stress literature to inform our research with relevant knowledge of the problem space (Vom Brocke et al. 2020). Additionally, we employ a literature review on extant MSA design knowledge to evaluate our research’s importance and novelty from an ex-ante perspective (Sonnenberg and Vom Brocke 2012; Venable et al. 2016). This subsection gives additional details on the examined body of literature. Although the literature review yields a total of 136 MSA instantiations for different intended applications, MSA design knowledge is highly dispersed and difficult to access for researchers and practitioners engaged in assessing individuals' stress in mobile settings. This also manifests in the observation that only a few MSA studies inform their design with extant design knowledge from other studies, which corresponds to a major limitation of current DSR practice (Vom Brocke et al. 2020). Thus, we argue that our design objective, the production of generalized and reusable MSA design knowledge, is highly relevant and worth exploring.

Inspired by Meth et al. (2015), the design knowledge presented here comprises several components. First, we derive relevant *design requirements* for MSA systems from exemplary literature (presented in section on the theoretical background). Then, we thoroughly analyze the MSA literature base and consolidate the formerly dispersed design knowledge consisting of an *abstract blueprint*, *design principles*, and *design features*. This step aims at formatively evaluating the feasibility and applicability of an MSA design theory for facilitating the implementation of MSA (Venable et al. 2016). We conceptualize an *abstract blueprint* based on architectural commonalities of the MSA instantiations and employ a taxonomy development approach (Nickerson et al. 2013) to derive seven *design principles* from design-related learnings reported in the MSA studies and to identify six *design features* of extant MSA instantiations. The design features detail how the design principles can be implemented into a specific MSA system and tailor the MSA system to its intended application. Each design feature can be implemented in various ways. Based on the design features, we subsequently present archetypical MSA systems identified in a cluster analysis investigating what combinations of design features prevail in the literature.

Building upon this theory-driven MSA design knowledge base, we collect practical knowledge by developing five MSA instantiations using prototyping (March and Storey 2008) and action design research (Sein et al. 2011). Each of the five prototypes has a different intended application and exhibits a specific combination of design feature implementations. Our prototyping activities serve to evaluate the practical utility, suitability, and generality of the design theory (Venable et al. 2016) by demonstrating that instantiations of MSA for different intended applications is possible using the accumulated design knowledge. Lessons learned during these prototyping activities suggest that design features and design requirements interact with each other, meaning that trade-offs might be necessary depending on the intended application. We present these trade-offs in lessons learned from the implementation of five prototypes. Additionally, we employ the prototypes in laboratory and field studies to summatively evaluate the design theory's applicability and usefulness for developing effective and suitable MSA instantiations (Venable et al. 2016).

Finally, building on the design knowledge presented in this research, we compose a design theory following Jones and Gregor (2007) and conclude with a short discussion of the design theory's theoretical value using widely adopted criteria for theories in the IS field (Gregor 2006; Gregor and Hevner 2013; Jones and Gregor 2007; Vom Brocke et al. 2020).

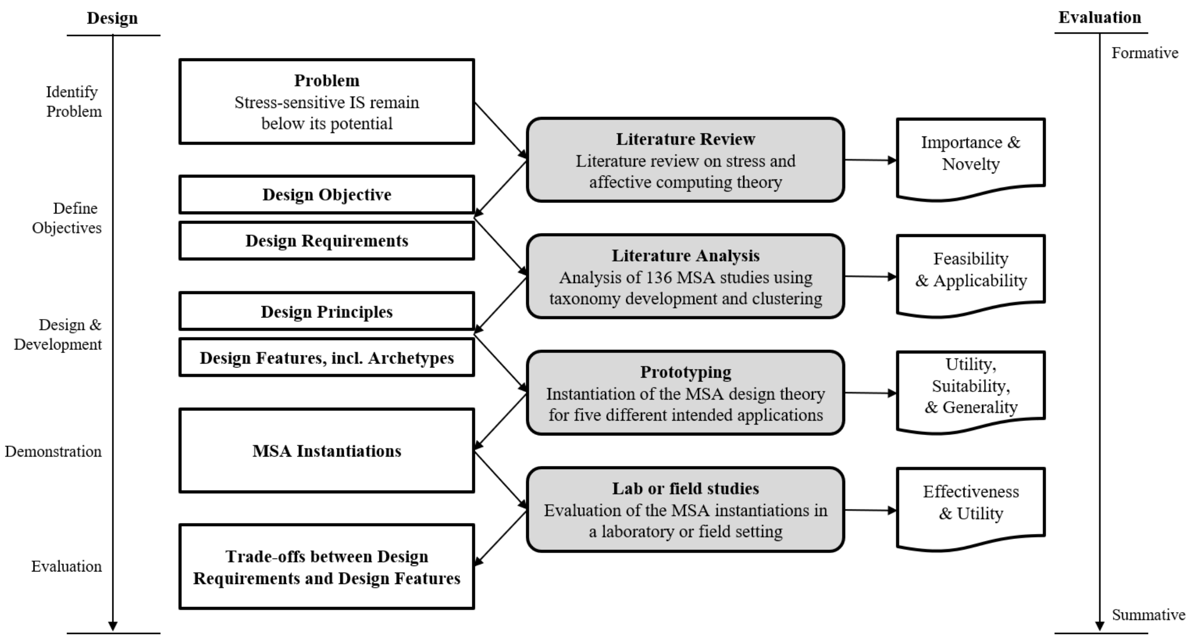


Figure 17: Research Process and Deliverables

Body of Literature

An extensive literature analysis of publications in the context of MSA builds the foundation for the identification and consolidation of design knowledge on MSA. We identify relevant MSA publications using two different ways: First, we start our search with the existing literature reviews on MSA introduced in the previous subsection and include the 55 referenced publications into the relevant MSA literature basket. Second, we complement these studies with a structured literature search in the AIS Senior Scholars Journal Basket (MISQ, ISR, JAIS, JMIS, EJIS, ISJ, JSIS, JIT) and all outlets of the IEEE Xplore. We limit our search to research articles on the assessment, detection, determination, or recognition of stress (the first two steps in the literature analysis revealed that the words assessment, detection, determination, and recognition are used synonymously in literature) using mobile or smartphone-based information systems or technology in the context of humans, people, users, or individuals (also used interchangeably in literature). This results in the following search string: stress AND (assessment OR detection

OR determination OR recognition) AND (mobile OR smartphone OR technology) AND (human OR people OR user OR individual). We consider only studies from 2010 and later because stress detection gained substantial attention only since then and exclude all studies that refer to stationary medical devices or are designed to work only in a certain location. This search resulted in an additional list of 81 studies discussing MSA. For the complete coding, please see https://figshare.com/s/3372ee6902eec19c1bc0.

Design of Mobile Stress Assessment Systems

As described in the previous section, various publications have demonstrated the feasibility of MSA for different intended applications. Building on this body of literature, we aggregate and leverage existing scholarly design knowledge in three ways: First, we analyze the state-of-the-art of existing MSA instantiations to identify structural commonalities and build an abstract blueprint that demonstrates the components and general architecture of MSA systems. Second, we condense lessons learned from extant MSA publications and derive seven design principles that serve as good practices for designing MSA. Third, we investigate which design features different MSA instantiations use to implement the design principles specifically for their intended application and identify six overarching features with three to five ways of implementing them. The following sections present these contributions in the described order.

Design Blueprint

The literature analysis yielded general architectural components of MSA that are common in MSA instantiations and form a simple blueprint which interrelates these components. Even though they are neither new in literature nor overly surprising to practitioners, we perceive that a general architecture and a clear description of the components help a common understanding of MSA.

The prevailing insight gained from the literature analysis is that the components of MSA do not form a purely technical system but a sociotechnical system. Five major components are present in all studies: (A) the user and its environment, (B) data collection via sensor technology, (C) data storage, (D) data pre-processing, (E) data modeling for stress assessment, and (F) some reporting of the results. Figure 18 illustrates their interrelations. There are two possible transitions between the technical and the social part of the system: First, sensors digitalize information on the user and its environment into computer-processible data. Second, the results reporting loop back to the user to make the determined stress usable for the intended application, for example, to assist individuals in dealing with stress.

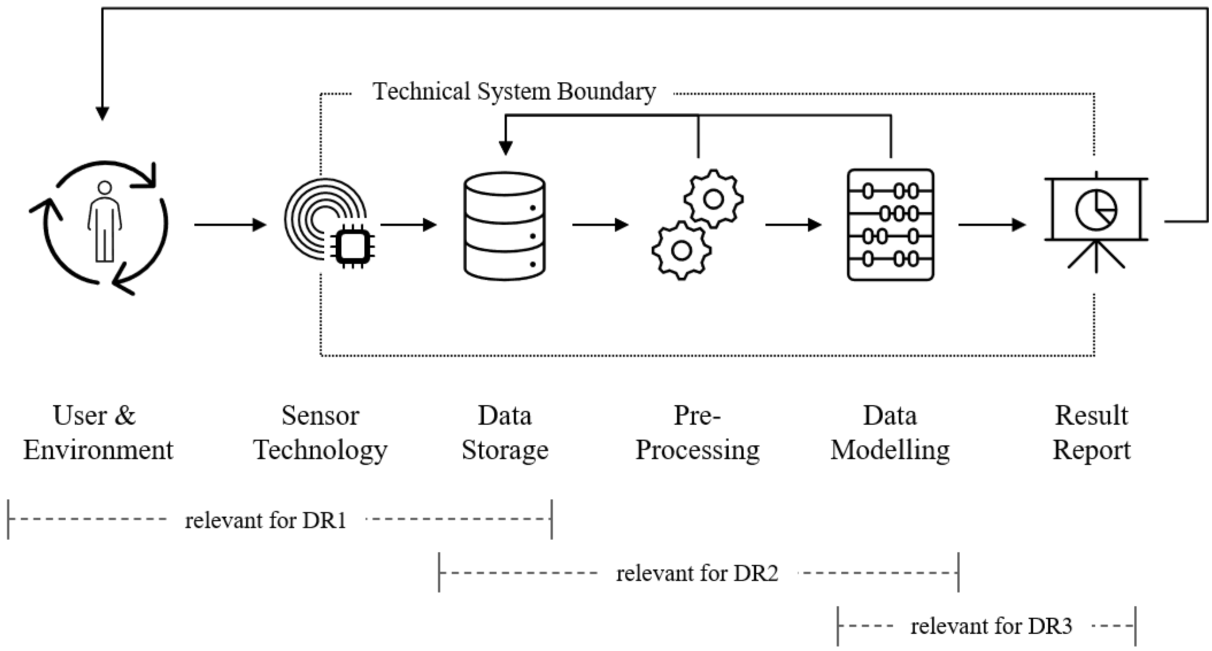


Figure 18: Illustration of the Architectural Components Forming a Simple Blueprint

(A) User and environment: As described in the theoretical background, human physiology (Cho et al. 2017; Singh et al. 2011), human behavior (Lawanont and Inoue 2018; Liao et al. 2005), human perception (Gaggioli et al. 2013; Rodrigues et al. 2015), and environmental conditions (Garcia-Ceja et al. 2016; Lane et al. 2011) can provide valuable input to stress assessment of individuals (Cohen et al. 1983; Traina et al. 2011; Weisman et al. 2016). This enables a comprehensive view of stress-related factors, which is vital for MSA and indicates both stressors and strains. Although DR1, due to the many facets of stress, refers to data about the user and its environment, we find in our literature analysis some systems that do not consider both, but focus for example solely on the user.. Besides sensing, some systems incorporate a second interaction point with the user and apply the processed data to provide behavioral or environmental feedback. Although MSA systems could also benefit from direct interaction with the environment to correct stressing environmental conditions like noise pollution or stroboscopic light, currently, no system incorporates actuation on the environmental level due to technological boundaries. However, smart home technologies' increasing pervasiveness could help overcome difficulties with automatic environmental adjustments to reduce people’s stress.

(B) Sensor Technology: In MSA, data is the foundation for all analytical activities that assess stress. According to the principle “Garbage in – garbage out”, sound data is a vital determinant

of MSA performance. Thus, significant thought should be put into the specification of what data to collect, how to collect it, and how at the same time, to ensure the validity of the data promoted in DR1. Our literature analysis found that a multitude of different approaches to sensor-based data collection in MSA exist. In our terminology, ‘sensor’ refers to every single data source that automatically gathers relevant information for MSA. These approaches range from self-reported data manually provided by the user up to sophisticated sensor fusion models that automatically combine data from different sensors using machine learning techniques to create new variables (Gimpel et al. 2015). Approaches based on self-reported data include, for example, periodic questionnaires or the manual input of stress-relevant data (Rodrigues et al. 2015). While these approaches are rather easy to implement, they also demand for strong user engagement. Consequently, we found that current research's focal point lies in approaches that use hardware and software sensors, automatically collecting information on the user and its environment. Instead of relying on the user’s steadiness, the performance of these approaches highly depends on the adequate choice of sensors (Greene et al. 2016). Hardware sensors (e.g., microphone (Gimpel et al. 2015) or accelerometer (Garcia-Ceja et al. 2016)) often provide powerful capabilities on sensing environmental information (Ollander et al. 2016; Zhao et al. 2013) or human physiology (Adnane et al. 2011) but only occasionally allow to draw direct conclusions on the user’s behavior (Bauer and Lukowicz 2012; Gjoreski et al. 2015). Software sensors capture data on the application level and thus have easier access to behavioral data, for example, in the number of incoming text messages (Bogomolov et al. 2014) or the degree of social interaction based on nearby Bluetooth devices (Lu et al. 2012). Both types of sensors can be attached to a single device (e.g., a smartphone (Ciman et al. 2015)), distributed over multiple devices (e.g., a smartphone and a wearable (Zenonos et al. 2016)), or integrate information from other IS (e.g., online social networks (Lee et al. 2012)). Further, sensors can be triggered either by time (e.g., continuously, every 5 minutes, once) or by event (e.g., incoming text message, significant change of location) (Pioggia et al. 2010). With all these possibilities, the appropriate design of the data collection part of an MSA system is vital. While data with high resolution allows deeper analyses and can result in higher stress assessment accuracy, this performance boost often comes at the cost of battery life, data transmission volume, and, consequently, user acceptance. If sensors are distributed across different devices, additional factors like time synchronization may need to be considered as the clocks of two devices generally slightly differ. Time-triggered sensors distributed across these devices should be synchronized to ensure comparability over time and between sensors (Adams et al. 2014).

(C) Data Storage: The valid data on the user and its environment (DR1) collected in *(B)* needs to be stored to enable a reliable data analysis (DR2). This can be performed locally on the device that captures sensor data (Bauer and Lukowicz 2012; Massot et al. 2012), on external storage attached to the system via a wired or wireless connection (Mohino-Herranz et al. 2015; Zhang et al. 2012), or on a cloud platform (Berndt et al. 2011; Gaggioli et al. 2013), which is particularly relevant, when sensors are distributed across multiple devices as described in *(B)*.

(D) Data Pre-Processing: As stress assessment requires a set of sensor observations, raw sensor data usually does not directly qualify for the model generation but needs to be pre-processed to ensure proper accuracy (DR2). In doing so, the systems must aggregate sensor data over time and apply various transformations, which need to be defined before the model generation and stress assessment (Bakker et al. 2011; Ben-Hur and Weston 2010). The design choices relevant for this component include selecting an appropriate approach to data aggregation, the definition of how to deal with missing values or the decision on a method for removing outliers in variables (Fernandez and Picard 2003).

(E) Data Modelling: Subsequently, statistical model building allows for assessing stress based on the acquired and transformed data points (Picard 2003). In this step, the selection of statistical models appropriate for the application scenario at hand is of vital importance (Salai et al. 2016), especially when it comes to sophisticated scenarios that require a rapid, near real-time assessment of stress and involve calculation- and resource-intense tasks like updating the model with new observations (Zubair et al. 2015). Sensor fusion – that is, the generation of new variables by combining data from different sensors – can improve robustness and confidence (DR), and reduce ambiguity and uncertainty of the model (Xiong and Svensson 2002) by providing a more valid representation of the user (Chen et al. 2014), their environment (Huh et al. 2014; Lu et al. 2012), and the interaction between both (Zenk et al. 2014). Finally, on the one hand, the procedure for modelling the data also has an influence on what information can be made available to the user later on, and, on the other hand, the expected output of the assessment also determines which algorithms can be considered for processing the data. For example, depending on whether the stress level should be reported on a binary or ordinal scale, different data modeling approaches come into play (DR3).

(F) Result Report: Finally, the stress modeling results can be communicated to the user to foster stress coping and management. However, it is important to distinguish whether the report's recipient is the user about whom the data is collected or whether the recipient is a third person

or system. The latter is the case, for example, if a third person is responsible for stress management, as is the case with Sandulescu and Dobrescu (2015) on monitoring firefighters. Accordingly, it is important to think about the presentation of the stress assessment results (DR3).

Design Principles

Many of the MSA publications in our body of literature produce knowledge chunks on lessons learned during their design and development process reported in the respective discussion or conclusion sections. We analyzed these lessons learned using taxonomy development methods (Nickerson et al. 2013), which suggest an iterative process combining the empirical inference of conceptual similarities and differences using relevant examples and the distinction of examples using existing conceptual information. Therefore, we divide the literature body into three parts used in the respective iterations: (1) the extant MSA literature reviews, (2) the original studies referenced in the literature reviews, and (3) additional and newer studies identified by own literature search.

In a first step, we use this approach to derive seven design principles that provide guidelines for meeting the design requirements when creating an MSA system. The design principles serve as principles of form and function as described by Jones and Gregor (2007) and describe general aspects of designing an MSA system. The design principles are intended to guide future researchers and practitioners on important design decisions that should be considered when developing an MSA., The mapping of the design principles to the design requirements is depicted in Figure 19.

(DP1) Consider a wide range of facets of the user and their environment to respect the diversity of stress: Stress is multifaceted. It can originate from psychological (e.g., overload, life events, technology) as well as physical (e.g. noise, temperature, lighting) stimuli (Lu et al. 2012; Riedl and Javor 2012). To take this versatility into account, it is essential to capture all relevant facets for the predefined MSA use case. Examples of these are users' location history, neurophysiological activity, smartphone or computer usage, medical history, or weather conditions amongst many others. It is preferable to cover more rather than fewer facets, since the fading out of aspects which turn out to be less relevant is usually unproblematic. For instance, user location data can provide information on both mobility and weather conditions. In addition, these data can be collected unobtrusively. Even if these data should not be included in a model used later for stress assessment, their collection does not cause unnecessary effort or damage. DP1 recommends considering as many different facets of the user and their environment as possible for

the objective of MSA. Thus, it suggests how valid data about the users and their environment can be collected and contributes to DR1.

(DP2) Choose and place sensor technology according to the predefined use case to meet the requirements for the individual stress assessment scenario: To satisfy the system quality criteria of resource consumption (DR4) and user acceptance (DR6), it is crucial to adapt the sensor technology used for MSA to the individual assessment scenario. The pre-defined use case determines this scenario. Depending on this, the suitability of the used sensor technology can vary significantly. For instance, a system that enables MSA for firefighters in action (Sandulescu and Dobrescu 2015) requires a far different selection and placement of sensor technology than a system for smartphone-based stress assessment in daily life (Gjoreski et al. 2015). The first scenario involves using a smart shirt to measure firefighters' heart rate, environmental humidity, and temperature as well as a microphone to detect communication and a motion sensor. In the second scenario, motion data, microphone data, and environmental parameters (i.e., light intensity) are also used for MSA. However, they are combined in a single everyday device (i.e., a smartphone). This example shows that the selection and placement of sensor technology vary greatly between different use cases, even if similar facets of the user and their environment (DP1) are applied for MSA. Overall, DP2 also aims to gather valid data about the user and their environment (DR1) by addressing the use of sensor technology according to the MSA use case.

(DP3) Select reasonable query times and intervals for all sensors to provide a basis for reliable stress detection with low obtrusiveness: Some physiological markers react differently when users are exposed to short-term or long-term stress. The heart rate, for example, increases in short-term stress but decreases in chronic stress (Schubert et al. 2009). Also, different parts of the human brain and body are activated in a temporal order. Thus, it takes some time until the stress reaction is measurable. This indicates that sensor design is vital if the system is designed to capture the biological response to stress. DP 3, therefore, recommends selecting meaningful query times and intervals for all sensors to ensure reliable stress detection and accurate MSA results (DR5). The selection should also comply with unobtrusive stress detection, as this also affects resource consumption and user acceptance (i.e., DR4 and DR6). An example of the reasonable selection of query times and intervals is a study on stress detection for public bus drivers (Rodrigues et al. 2015). Specific self-report measures complemented continuous physiological measurements. Together with DP1 and DP2, this design principle aims at gathering valid data about the user and their environment (DR1).

(DP4) Comply with users' routines and habits to ensure high acceptance of the MSA system: One of the most important characteristics of a system to achieve high user acceptance is unobtrusiveness. Unobtrusiveness and thus user acceptance can be achieved not only by a well-considered selection and placement of sensor technology (DP2) and reasonable query times and intervals for stress detection (DP3), but also by designing the system according to the users' routines and habits. As stated in the extended Unified Theory of Acceptance and Use of Technology (UTAUT2, Venkatesh et al. (2012)), habit is positively related to usage behavior. Designing an MSA system to fit its users' routines and habits allows system usage to become routine as well. This results in a positive impact on usage behavior through acceptance. For instance, Ciman and Wac (2018) developed an MSA approach building on smartphone gesture analysis. The approach detects stress from tapping, scrolling, swiping, or writing on a smartphone touch screen. As smartphone users perform these actions on their smartphones anyway, a system following this approach would perfectly fit their routines and habits. Overall, this design principle satisfies DR1 since user acceptance is a prerequisite for regular system usage and thus the collection of valid data on the user and their environment.

(DP5) Fuse data from multiple sensors to comprehensively grasp the user and their environment: To get a comprehensive view for the intended application, system designers should plan, which aspects of the user and its situation complement each other for stress assessment in their application (Adams et al. 2014; Ayzenberg et al. 2012) and combine these aspects by fusing data from multiple sensors. This is not limited to data from sensors attached to the user, but also comprises data acquired from the user's surrounding environment. As stress is a complicated part of human life, solely analyzing raw data is not sufficient. Already simple descriptive statistics may provide relevant insights into users' behavior (e.g., deviation of a daily routine, behavior varying depending on the location). Thus, preprocessing the fused sensor data is an important foundation for stress assessment. Overall, DP5 is a proposal to calculate a reliable value for users' stress level (DR2) while ensuring accurate MSA algorithms (DR5).

(DP6) Personalize stress assessment to consider the individual causes and consequences of stress: There are three different ways to model the interrelations between sensor data and stress: build (1) a general model (generated using data from multiple users), (2) a personal model (generated using data from one user), or (3) a hybrid model that initializes personalization with the general model (Garcia-Ceja et al. 2016). To account for the individual causes and consequences of stress in an MSA scenario, this design principle recommends using a personal or hybrid stress model. An important tool to implement personalization in MSA systems is using

historical data on the users' stress as a proxy for current stress states. This can be realized, for example, by introspection (i.e., by asking users how they feel at certain points in time) (Gimpel et al. 2019a). Current literature indicates that stress depends on the remaining resources, which can be approximated using the previous stress level and recent stressors. This indicates that stress assessment can benefit from historical data on stressors, strains, and the resulting lack of resources (Adams et al. 2014; Bogomolov et al. 2014). Together with DP5, this design principle suggests a way for an MSA system to calculate a reliable value for users' stress levels (DR2).

(DP7) Report a measure of stress to the recipient in an intuitive and understandable way to enable efficient assessment: The final building block for a complete MSA system is reporting the assessment results to a recipient. This design principle satisfies the requirement of transparently reporting the calculated stress level of an MSA (DR3). Further, the design principle is connected to DR5, which requests the used algorithms in an MSA system and, thus, the reported stress measure to be accurate. Also, the reported result must be intuitive and understandable to ensure user acceptance (DR6). However, the recipient mentioned in this design principle does not necessarily need to be the user of the MSA system. For instance, the MSA system for firefighters in action (Sandulescu and Dobrescu 2015) features a *Remote Processing Unit*, which enables remotely reporting the calculated stress measure to the mission supervisor. The MSA platform *deStress* (Zhang et al. 2012) provides both a device-based and web-based graphical user interface, allowing users to view, manage, and share their stress data with medical professionals. In both examples, the recipients of the reported stress measures are not necessarily the system users. The reported stress measure itself depends on requirements derived from predefined use cases.

Design Features

While the design principles presented in the previous section describe specific recommendations for the design of MSA systems, they do not yet specify how these aspects can be implemented into a specific MSA system. Therefore, we use the same taxonomy development approach also to investigate how the MSA instantiations in our body of literature tailor the system to their specific intended application. This process yields six overarching design features described in the following. Each of the design features can be implemented in various ways and relates to the implementation of one or more design principles. These relations are visualized in Figure 19.

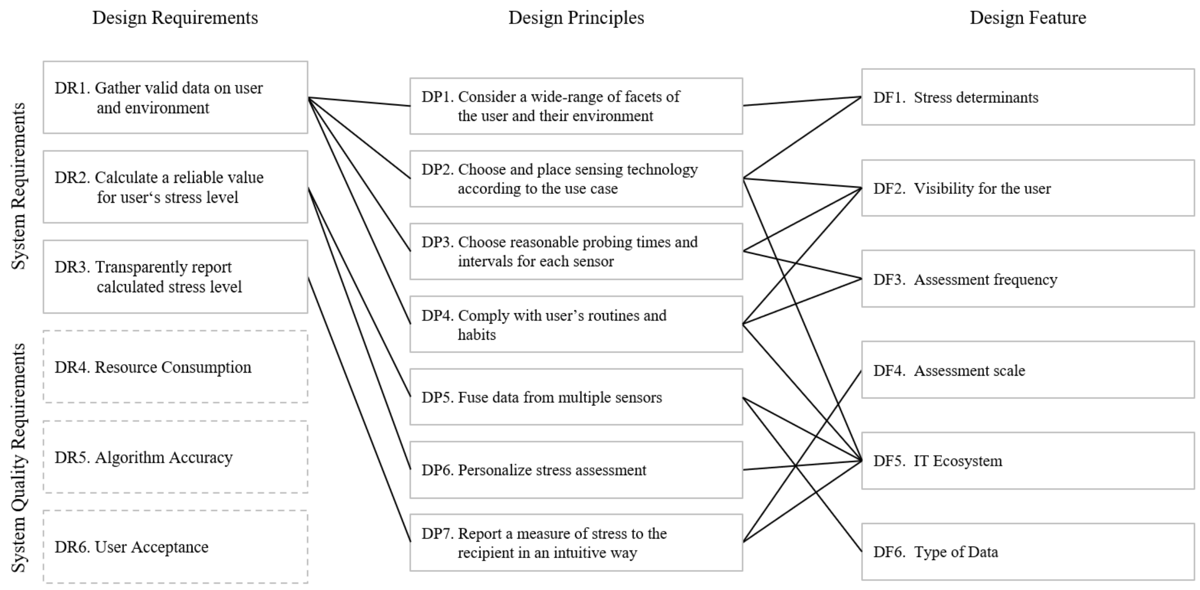


Figure 19: Dependencies between Design Requirements, Design Principles, and Design Features

(DF1) Stress Determinants: MSA draws information from various sources, which we call *stress determinants*. This design feature refers to the use of different data on the user and their environment to assess stress. Hence, the selection of stress determinants implements DP1 by determining the considered range of user-related and environmental facets. Further, it is linked to DP2 as the choice of suitable stress determinants results from meeting a scenario's individual requirements in terms of sensor technology. Although each MSA system employs stress determinants for assessing stress, there are different possible implementations. Some systems use introspection methods to prompt the users for input on their stress perception or feelings at certain points in time, for example, by stress diaries helping individuals record differences in stress over time (Aigrain 2016; Wang et al. 2014). Some systems use introspection in combination with other stress determinants such as biological or behavioral symptoms of stress. *Biological symptoms* of stress include all bodily changes associated with automatic, mostly unconscious, biological processes such as heart rate, blood pressure, sweating, or pupil dilation. Many MSA systems examined, therefore, rely on consumer-grade biosensors. While some of these systems only biological symptoms only use biological symptoms as a stress determinant, others combine biological symptoms with other stress determinants such as introspection (Rodrigues et al. (2015) or *behavioral symptoms* (Pioggia et al. (2010). In this, behavioral symptoms such as reduced typing accuracy (Gimpel et al. 2015), characteristic gestures (Lefter et al. 2016), or voice modulation (Ferreira et al. 2009) are a common additional stress determinant. While we do not find any MSA systems using exclusively *environmental* data such as weather

information or ambient noise to infer external stressors affecting the individual, many systems include environmental information to improve assessment performance (Mayya et al. 2015; Plarre et al. 2011) and thereby implement a *mixed* form of stress determinants.

(DF2) Visibility to the Users: Conventional methods of stress assessment involve subjects to undergo medical tests (e.g., measurement of cortisol levels in saliva), think about their perception (e.g., questionnaires), or be mentally aware (e.g., due to wearing unaccustomed devices like custom-made heart trackers). MSA systems hold the potential to achieve a high degree of independence of location, attention, and thought if required by the use case (Gimpel et al. 2015). Therefore, in our literature analysis, we find MSA systems featuring different levels of *visibility to the user*. We define this design feature as the degree to which an MSA system is integrated into an individual's life and identify three design principles that interrelate with this design feature. First, the desired level of user visibility is related to sensor technology choice and placement (DP2). Second, the shaping of query times and intervals (DP3) depends on the system's visibility (e.g., when using questionnaires). Finally, DP4 suggests complying with users' routines and habits to ensure high user acceptance. This can be achieved by keeping an MSA system's visibility to the users as low as possible. There are three conceivable levels of *visibility to the user*. An *obtrusive* way of implementing an MSA system requires the user's attention. Typical characteristics of obtrusive MSA systems are questionnaires (Ferdous et al. 2015) on smartphones to trigger ecological momentary assessments (Chang et al. 2011; LiKamWa et al. 2013). Some MSA systems do not require the user's attention but still require them to adapt their habitual routines (e.g., by wearing additional devices). These *unobtrusive* systems employ long-range devices to assess the stress level, e.g., video cameras (Elgharib et al. 2015) or wearable trackers to sense heart rate (Chang et al. 2011; Lu et al. 2012). The most natural way to assess stress is *life-integrated* stress assessment. Life-integrated MSA systems refrain from altering users' daily routines and integrate themselves into their daily routines without interference. This can be achieved, for example, by using only the smartphone for stress assessment. However, some instantiations demonstrate that this may also require additional knowledge on the user's location (Lane et al. 2011) or connectivity to the internet (Lee et al. 2012).

(DF3) Assessment Frequency: There are two different types of stress from a temporal perspective: chronic stress (referring to a long-lasting endurance of stress) and acute (short-term stress). While chronic stress constantly exposes people to a certain level of stress, for most people the level of acute stress varies over time depending on their availability of resources and the load induced by environmental stressors. The system's *assessment frequency* depends on which of

the two types of stress an MSA system addresses. Determining an appropriate assessment frequency when implementing an MSA system relies on two of our above-presented design principles. First, selecting reasonable query times and intervals (DP3) is an essential prerequisite for implementing a suitable assessment frequency. Second, it is crucial to best possible comply with users' routines and habits to ensure the viability of the respective assessment frequency.

There are three possible ways of implementing this design feature. First, if the use case targets a long-range assessment of stress (Fehrenbacher 2017; Unsoo et al. 2015) or involves analyzing treatment effects in lab studies (Costin et al. 2012), an elicitation of stress in *regular intervals* of weeks or months is sufficient. Second, to evaluate the effects of stress interventions targeting chronic stress or investigate extended episodes of acute stress (Wang et al. 2014), stress assessment is required to *retrieve reliable values for the current level of stress continually*. Continually stress assessment requires collecting relevant data on an approximately daily basis. Third, complex scenarios that perform just-in-time interventions (Nahum-Shani et al. 2015) like stress-sensitive adaptive enterprise systems (Adam et al. 2017) pose even higher requirements and demand for *continuous* stress assessment to obtain real-time stress levels.

(DF4) Assessment Scale: Stress can be reported in different levels of granularity. The design feature *assessment scale* specifies which requirements the assessment results must meet concerning the level of detail. Implementing a specific assessment scale in an MSA system addresses DP7 in the way that it determines what is reported to the respective recipients. The choice of a suitable granularity supports communicating the measure of stress intuitively and contributing to efficient stress assessment. We identify three methods for implementing this design feature. Stress can most easily be modeled as a *binary* variable differentiating between 'stress' or 'no stress' (Bogomolov et al. 2014; Chen et al. 2014; Hovsepian et al. 2015). While this distinction might be sufficient for many use cases, other scenarios require a higher granularity level for stress intensity. For example, this cane achieved using an *ordinal* scale with three or more increments (Garcia-Ceja et al. 2016). *Metric* scales allow an even more fine-grained differentiation of stress levels (Gao et al. 2014; Zhang et al. 2012). The 4-item Perceived Stress Scale (Cohen et al. 1983), for example, assesses stress on a scale ranging from 0 to 16 and allows for the recognition of subtle changes in the user's stress. However, the assessment scale used in an MSA system should be chosen to best meet the use case requirements as assessment accuracy generally decreases with an increased level of detail (Lawanont and Inoue 2018; Mohino-Herranz et al. 2015).

(DF5) IT Ecosystem: The design feature *IT ecosystem* specifies the scale of an MSA system's technical implementation. In this, it refers to the magnitude with which the system spans across multiple devices and technologies. Since the IT ecosystem is a superior building block of an MSA system, its implementation is connected to five of the presented design principles. The selection and placement of sensor technology (DP2) affect the characteristic of the IT ecosystem. Also, complying with users' routines and habits (DP4) and the implementation of sensor fusion (DP5) impose demands on the IT ecosystem. Finally, personalizing stress assessment (e.g., through introspection, DP6) and reporting the results of stress assessment (e.g., through graphical user interfaces on special devices, DP7) impact the scale and architecture of a respective IT ecosystem. We identify three distinct ways to implement this design feature. As our design blueprint demonstrates, MSA systems consist of several components responsible for gathering sensor data, storing gathered data, processing the data to qualify it for stress assessment. These components must be capable of communicating with each other. However, they do not necessarily have to operate on a *single device*. While several MSA systems target such all-in-one solutions (Bauer and Lukowicz 2012; Lane et al. 2011) running on a single device, most MSA systems developed up to now distributes the components across multiple mobile devices. These systems generally exhibit a distributed system architecture that connects *multiple devices using local communication* protocols like Bluetooth or NFC (Liao et al. 2005; Singh et al. 2011). Some use cases require an even more large-scale approach connecting devices and components via internet-based protocols (e.g., using cloud services) to form *Multi-Platform-Systems* (Ayzenberg et al. 2012; Berndt et al. 2011). Contrary to systems using local communication, multi-platform systems enable integrating location-dependent sensors in smart homes or dynamically incorporating omnipresent, powerful sensors such as wearable devices for tracking biosignals.

(DF6) Type of Data: MSA systems differ in the *type of data* used for stress assessment. Stress is highly individual. Thus, its assessment requires collecting information describing the user as detailed as possible. Naturally, this data has the potential to raise privacy concerns. Consequently, MSA systems must implement high security and privacy standards to best possibly eliminate user concerns (Adams et al. 2014; Miyamoto et al. 2016). Aligned with traditional non-functional requirements for medical IS (Meulendijk et al. 2014), these factors (i.e., the individuality of stress, the risk of privacy concerns, and high security standards) constitute boundaries for the design of MSA systems. Since the implementation of this design feature is strongly connected to the aggregation level of the used data, it relates to DP5, which proposes

the fusion and aggregation of sensor data for a comprehensive view on MSA system users and their environment. The specific security and data privacy standards for an MSA system strongly depend on the type of data used in the MSA system. If the system collects exclusively *non-personal data* from the environment (Betti et al. 2018), there are little privacy concerns that need to be addressed. However, if a use case additionally demands for *aggregated personal data* (e.g., number of incoming calls; average duration of phone calls), steps must be taken to increase data security and privacy. The most sensitive type of data in stress assessment is *raw personal data*. This form of data includes, for example, message contents (Ayzenberg et al. 2012), video data (Cho et al. 2017), or data resulting from sentiment analysis (Gimpel et al. 2015). MSA systems building on this data, therefore, require even higher protection standards.

Overall, the design features presented here detail how MSA design can be put into practice. Based on this, designers of MSA systems can reflect on how to implement these design features according to the specific requirements of their system's intended application. Table 16 summarizes the design features and ways of implementing them.

Design Feature		**Manifestations** (mutually exclusive, collectively exhaustive)				
DF1	Stress Determinants	Environment (0)	Introspection (2)	Biological Symptoms (62)	Behavioral Symptoms (22)	Mixed (50)
DF2	Visibility for the User	Obtrusive (45)	Unobtrusive (78)	Life-integrated (13)		
DF3	Assessment Frequency	Regular Intervals (36)	Continually (56)	Continuously (44)		
DF4	Assessment Scale	Binary (67)	Ordinal (54)	Metric (15)		
DF5	IT-Ecosystem	Single Device (21)	Multiple Devices using Local Communication (88)	Multi-Platform-System (27)		
DF6	Type of Data	Non-Personal Data (4)	Non-Personal and Aggregated Personal Data (73)	Non-Personal and Raw Personal Data (59)		

Notes: The numbers in parentheses refer to n = 136 MSA instantiations and indicate how many of the identified systems exhibit the given characteristic

Table 16: Ways of Implementing the Design Features

Archetypes

The taxonomy development reveals valuable insights into the design of MSA by producing both general design principles and specific design features as levers that help tailor the system's design to the specific intended application. To achieve higher-level insights into MSA systems' current diversity, we investigate the characteristics of the published MSA instantiations in more detail.

To analyze this systematically, we perform a hierarchical cluster analysis that aims to identify MSA archetypes by clustering all 136 MSA studies according to their manifestation of the design features using divisive clustering. The elbow method (Thorndike 1953) reveals that five clusters are an appropriate choice of clusters. Table 17 presents the footprints of each archetype within the design feature classification. This footprint shows the archetype's prevailing design feature (occurring with a frequency of at least 50%). Each archetypes' specifics are highlighted in blue.

	Data-Sparse Assessment	Sensor-Enriched Assessment	Wearable-Focused Assessment	Multi-Facet Assessment	User-Focused Assessment
Number of Studies	48	48	6	23	11
Stress Determinants	Biological Symptoms	Biological Symptoms	Biological Symptoms	Mixed	Behavioral Symptoms
Sensitivity of Data	Non-Personal and Aggregated Personal Data	Non-Personal and Raw Personal Data	Non-Personal and Raw Personal Data	Non-Personal and Raw Personal Data	Non-Personal and Raw Personal Data
Visibility for the User	Unobtrusive	Obtrusive	Unobtrusive	Life-Integrated	Unobtrusive
Assessment Frequency	n.c.	n.c.	Continually	Continually	Continually
Assessment Scale	n.c.	Binary	Metric	Ordinal	Binary
Ecosystem	Multiple Devices	Multiple Devices	n.c.	Multi Platform	Single Device
Examples	Ahmed et al. (2016), Attaran et al. (2016), Cernat et al. (2017)	Chen et al. (2014), Wu et al. (2019), Momeni et al. (2019)	Boateng and Kotz (2016), S et al. (2020), Momeni et al. (2019)	Ciman et al. (2015), Dobbins and Fairclough (2019), Gimpel et al. (2019b)	Rachuri et al. (2010), Ciman and Wac (2018), Ashok et al. (2016)

Notes: blue cells indicate the archetype's essential characteristics); n.c. means that there is no dominant characteristic of the archetype for the design feature

Table 17: Archetypes of MSA Systems

In the following, we describe these archetypes in detail based on how strongly the clusters correlate and how clusters developed during clustering.

Data-Sparse Assessment: The first archetype, data-sparse assessment, differs from the other archetypes in the particularity that those MSA systems primarily process data about the user's environment and, in the case of personal data, store and process them only in aggregated form while raw personal data is discarded. The data is primarily collected via additional devices that, among other things, analyze biological symptoms and store the results. The system acts mostly unobtrusively and does not require interaction with the user. Examples include Ahmed et al. (2016) who focuses on respiratory patterns in stressful and relaxed situations, Attaran et al.

(2016) who combines different parameters from a self-developed physiological tracker and Pandey (2017) who use IoT devices to inform users about an unhealthy lifestyle and even alerts before any acute condition occurs.

Sensor-Enriched Assessment: The second archetype, sensor-enriched assessment, exhibits the distinctive feature that users are aware of the use of the MSA system and sometimes even need to adapt their behavior for its use. Here, too, the data is primarily collected and stored via additional devices that analyze biological symptoms and other data. In comparison to the first archetype, however, the classification into "stressed" and "not stressed" is paramount. Many of these systems aim to be as accurate as possible, use as many different sensors from various devices as possible to achieve this, and find application mainly in laboratory settings. Examples include Chen et al. (2014) who use a mobile spectrograph to capture hyperspectral imaging data to measure oxygen levels and then infer stress levels, Wu et al. (2019) who attach textile electrodes to a t-shirt and then use, for example, skin conductance and heart rate variability to determine the user's stress level, and Cernat et al. (2017) who also use the same two parameters as stress determinants and collects data on car drivers connected to different instruments.

Wearable-Focused Assessment: The third archetype, wearable-focused assessment, requires users of such systems to wear additional devices in the form of wearables that unobtrusively collect data. Compared to the two previous archetypes, those MSA systems provide metric results and are thus more detailed in the assessed level of stress, while at the same time being less accurate. Systems from this archetype are rarely represented in the literature despite their use of wearable devices. One possible reason for this is the detailed recording of the stress level on a metric scale, which is not the case in most other systems with biological systems as they primarily employ a binary classification. Examples of this are Boateng and Kotz (2016), who use the Amulete Wearable platform to extract data from a commercial heart-rate monitor and determine a stress level continuously and in real-time, S et al. (2020) who use a wrist wearable to record the condition of a physician during an operation, and Momeni et al. (2019) who record and process physiological data as part of a simulator for search and rescue operations.

Multi-Facet Assessment: The fourth archetype, multi-facet assessment, makes use of different stress determinants. Thus, in addition to the biological symptoms mostly used in the previous archetypes, data on the user's behavior, the environment, and other contextual information are also included. Accordingly, many different sensors are used, most of which are interconnected via complex system architectures. Compared to the previous archetypes, the stress level is mostly assessed based on an ordinal scale, for example, no stress, low stress, or high stress. Besides, systems belonging to this archetype are integrated into the user's everyday life and thus do not require any interaction or changes in the user's behavior. Thus, compared to the other systems, these systems offer the lowest potential for bias and contend with various robustness challenges. Examples include Ciman et al. (2015) who extract usage data from a smartphone (e.g., tap, scroll, wipe), Dobbins and Fairclough (2019) who collect various data points from drivers, and Gimpel et al. (2019b) who extract various sensors from a smartphone (e.g., GPS, text sentiment, number of calls) to infer stress based on data on the user and their environment.

User-Focused Assessment: The fifth and final archetype, user-focused assessment, is special in the finding that these systems focus on the behavioral changes that occur in stressful situations. The MSA system records how the user interacts with a device and tries to identify the state – in most systems of this archetype, the distinction between stressed and not stressed – based on a change in the interaction with the device. For this purpose, these systems typically collect data from devices that users already interact with intensively, such as the smartphone or the keyboard or mouse of a computer. Systems of this archetype are more frequent, especially in the new literature, since the smartphone has established itself as an everyday companion in advancing digitalization. Assessing stress based on smartphone data is facilitated by the trend that more and more companies are promoting the use of a single smartphone in private and professional environments in the course of bring-your-own-device strategies. This archetype differs from the previous one in the way that it is less integrated into the user's everyday life, might require certain adoptions of user behavior, and only a single device is used to collect, store, and process data. Examples of this are Rachuri et al. (2010) who use data from the smartphone to infer the user's emotional state and also extract various parameters from the voice, Ciman and Wac (2018) who analyze touchscreen operation in an advanced version of its prototype, and Ashok et al. (2016) who extract sound from a microphone to quantify stress in the human body using voice analysis.

Overall, we observe that most MSA systems aim to identify situations or contexts that are typically stressful and differentiate between more and less stressful phases, e.g., in games, in artificial tasks, or in school. Furthermore, the broad availability of cheap commodity devices (wearables) facilitates gathering data on biological markers and, thereby, fosters the development of MSA systems that investigate biological symptoms. Therefore, most systems incorporate biological features either exclusively or in combination with other stress determinants.

Only a few systems focus on neither biological nor behavioral symptoms. However, enabled by today's omnipresence of powerful sensors, such as smartphones or smart things, recently published MSA systems use multiple rich sensing capabilities to unobtrusively and continuously collect data on an individual and a situation. Finally, it is surprising that although there are already many systems demonstrating the feasibility of MSA, only few MSA systems facilitate the forming of new and individual systems and services.

Lessons Learned from the Implementation of Mobile Stress Assessment Prototypes

All findings presented so far are based on our extensive literature analysis of the existing knowledge on many different MSA instantiations. To gain practical experience by ourselves and produce insights into MSA system design, we design and develop five different variants MSA systems prototypically. This following section provides a brief explanation of the prototypes, while Appendix E describes the prototypes in more detail: it introduces a specific intended application, outlines the design and development of the prototype, presents the experimental study setting as well as relevant results, and discusses important learnings from this process.

Based on our experiences with the developed prototypes and the findings from the literature analysis, trade-offs between design features and design requirements are described that need to be considered when developing an MSA system.

Prototype Implementation

Two of our five prototypes (Appendix E.1 and Appendix E.2) target the real-time assessment of perceived stress using only the personal smartphone sensors to infer the user's stress level on an interval scale while being best-possibly integrated into their life. The second prototype complemented the first by personalizing the stress model used. Both prototypes can be assigned to the fourth archetype (multi-facet assessment). Another prototype (Appendix E.3) assesses an individual's stress level by measuring variations in the user's pupil dilation using video processing techniques solely storing the calculated pupil radii and discarding the video. Hence, this prototype is a representative of the data-sparse assessment archetype. The fourth prototype (Appendix E.4) examines the user's sleep behavior using only the smartphone for recording and processing purposes. Although the focus here is not stress per se, sleep behavior is a good indicator of stress. This prototype is thus an example of a user-focused assessment. The last prototype (Appendix E.5) is a general data collection framework that intends to simplify the connection of various sensor systems and takes over the acquisition, storage, and calculation. Since this prototype is not an MSA in the strict sense, it cannot be directly assigned to any archetype. It contains aspects of wearable-focused assessment due to the options for connecting various sensors and aspects of user-focused assessment due to the single-device architecture for recording, storing, and processing.

Although we have not prototyped every single archetype (prototypes from the archetypes of wearable-focused assessment and sensor-enriched assessment are missing), we gained helpful insights during the agile development process and within the studies that further understand the interconnectedness of blueprint, design requirement, design principle, and design feature and revealed possible trade-offs that have to be made in the design process.

Trade-offs between Design Features and Design Requirements

Table 16 indicates that each of the seven design features presented can be implemented in different ways. In introducing the design requirements, we have pointed out that meeting these requirements usually depends on the specific use case. Therefore, determining the manifestations of the design features implies trade-offs to best meet the system quality requirements for the respective MSA use case.

DF1. Selecting a specific way of implementing the stress determinants design feature implies trade-offs to meet the design requirements best. For example, an MSA system only capturing self-reported stress will not provide accurate results if a physiological stress marker is unknown to the user. A mixed approach (i.e., a combination of data originating from the users' environment, introspections, physiology, or behavior) may lead to increased algorithm accuracy (DR5). The gathered data cover different facets of digital stress, thus creating a more holistic picture. However, when using a mixed approach, an MSA system's technical resources consumption might increase due to the additional effort in data processing and analysis (DR4). Thus, a mixed approach should only be considered if the respective use case allows for higher resource consumption. Using a mixed approach might imply lower user acceptance because more data has to be gathered and evaluated (DR6). For instance, in the case of a smartphone app, this could involve granting the MSA system additional permissions, which might reduce user acceptance.

DF2. Also, the MSA system's visibility to the user (i.e., the grade of obtrusiveness) implies trade-offs between this design feature and the design requirements. The more obtrusive the MSA system is to the user, the more the accuracy of the used algorithms might be affected (DR5). If the users are strongly distracted by the system's obtrusiveness, a bias in assessing the users' stress can result. Under exceptional circumstances, the system's obtrusiveness itself could become a stressor for the user and thus corrupt the results. In addition to algorithm accuracy, determining an MSA system's visibility also affects user acceptance (DR6). Since no one enjoys using an obtrusive and thus interfering MSA system, a high degree of obtrusiveness is not beneficial to high user acceptance. When assessing the usage of our *prototype for life-integrated stress assessment*, we found that a high level of integration is a vital property of an MSA system for high user acceptance. However, complete life-integration of an MSA system with zero obtrusiveness can hardly be achieved. Therefore, the goal is to reduce the system's visibility as much as the intended application admits.

DF3. Determining the assessment frequency of an MSA system affects each of the properties addressed by the presented system quality requirements of moderate resource consumption (DR4), algorithm accuracy (DR5), and user acceptance (DR6). An MSA system featuring a high assessment frequency usually will require more technical resources than systems with a moderate or low assessment frequency. For instance, in the context of testing our *life-integrated stress assessment prototype*, we experienced that high sensor query rates resulted in an excessive discharge of the mobile devices' batteries. In contrast, a high assessment frequency results in more accurate assessment results due to a better measurement database. One way to mitigate this conflict might be to use high assessment frequencies in the initial phase of system usage to build a solid base of measurement data and lower assessment rates to reduce resource consumption. Finally, assessment frequency also affects user acceptance. In this context, the technical level is less relevant than the system directly prompting the user to make inputs for personalization purposes. Within the evaluation of our mobile *personalization of stress assessment prototype*, we discovered that the personalization of an MSA system should be as passive as possible. After achieving a sufficiently high level of personalization, requesting user input should be reduced to ensure user acceptance in the long run.

DF4. Choosing the assessment scale has implications for the algorithm accuracy of an MSA system (DR5). When using a continuous stress scale, algorithm accuracy can generally be increased over a binary scale, since more nuances can be represented in the assessment results. However, high variance in the results can cause a lack of reliability. A finer resolution of the assessment scale does not necessarily mean better algorithm accuracy. In certain intended applications, a binary classification might be sufficient. For instance, the evaluation of our *framework for automated data collection, storage, and preprocessing prototype* showed very good results for binary assessment. Overall, selecting a suitable assessment scale highly depends on the use and does not interfere with other system quality requirements except algorithm accuracy.

DF5. As for the assessment frequency, the specification of an IT ecosystem for the MSA system affects each of the properties addressed by the system quality criteria DR4, DR5, and DR6. The MSA system's resource consumption increases as the IT ecosystem grows in scale and complexity. An extensive IT-ecosystem (e.g., using a server-client architecture and multiple fused sensor devices) might imply a higher resource consumption such as increased energy demand. However, depending on the use case, a larger IT ecosystem may be an essential prerequisite for stress assessment. Therefore, technical resource consumption should not be taken as a general limit to the size of the used IT ecosystem. The scale of the IT ecosystem may also have an impact on algorithm accuracy. For example, integrating sensor fusion into an MSA system implies a higher complexity of the IT ecosystem but may result in an increased algorithm accuracy. In the evaluation of our *sensor fusion for sleep duration assessment prototype,* we thus could achieve a high classification accuracy greater than 90 percent. Finally, the scale of the IT ecosystem also has implications for user acceptance. For instance, client-server architectures that propose to store assessment results in the cloud might raise privacy concerns, resulting in decreased user acceptance.

DF6. The type of data used in an MSA system can affect algorithm accuracy (DR5). The more individualized the collected data is, the better the insight it can provide into the users' internal condition (e.g., physiological markers, self-reports). These detailed insights generally provide better algorithm accuracy than the use of more superficial, anonymous features such as ambient lighting or sound level. However, collecting sensitive data often results in privacy concerns and decreased user acceptance (DR6). For instance, our *life integrated stress assessment prototype* recorded and analyzed the content of received and sent text messages to detect stress signs. However, this caused considerable privacy concerns among the users, so we stopped storing the contents and processed them in coded form after a local analysis. Overall, user privacy should be highly prioritized, but trade-offs are required to achieve high algorithm accuracies.

To summarize the presented trade-offs between our six design features and the system quality requirements, Table 18 illustrates the positive or negative impacts of design feature manifestations on the system quality requirements. x indicates the occurrence of a trade-off between a manifestation of the design feature and the respective system quality requirement (i.e., DR4, DR5, or DR6).

Design Feature		DR4 Resource Consumption	DR5 Algorithm Accuracy	DR6 User Acceptance
DF1	Stress Determinants	x	x	x
DF2	Visibility to the User		x	x
DF3	Assessment Frequency	x	x	x
DF4	Assessment Scale		x	
DF5	IT Ecosystem	x	x	x
DF6	Type of Data		x	x

Table 18: Trade-offs between the Design Features and System Quality Requirements

Discussion

The previous sections presented essential design knowledge for the development of MSA. The construction of this design knowledge followed standard DSR methodology (Hevner et al. 2004; Peffers et al. 2007) and incorporated evaluation activities as a central part of the design process (Sonnenberg and Vom Brocke 2012; Venable et al. 2016). An ex-ante literature review demonstrated the novelty and importance of our research (Venable et al. 2016). By analyzing the literature, we consolidated extant design knowledge formerly dispersed across various MSA studies and derived design requirements, an abstract blueprint, design principles, and design features of MSA systems. The design requirements describe what MSA systems need to achieve. The abstract blueprint illustrates the common architecture of MSA systems. The design principles outline good practices on how to design effective MSA systems. The design features and their ways of implementing them detail how the design principles can be implemented into a specific MSA and tailored to its intended application. The archetypes arising from subsequent cluster analysis give further impressions how the design features are implemented in current practice. Overall, the literature analysis demonstrates the feasibility and applicability of an MSA design theory (Venable et al. 2016). Building upon this design knowledge, we produced new design knowledge from performing our prototyping activities, enriching the λ-knowledge base in terms of design entity knowledge. This new design knowledge comprises trade-offs between design requirements and the design features adapted to fit the specific intended application. These trade-offs have been found by developing five MSA prototypes for different intended applications. In this process, the collected design knowledge proved to be suitable and useful for MSA designed to be generalizable to various intended applications (Venable et al. 2016). The prototypes' evaluation in laboratory and field studies provides summative real-world evidence of the design theory's applicability and utility for developing effective and suitable MSA instantiations (Venable et al. 2016).

Combining the accumulated design knowledge, we compose a comprehensive design theory for MSA and extend the λ-knowledge base. This design theory extends the current literature on the topic and constitutes a mid-range theory for design and action (Gregor 2006; Gregor and Hevner 2013), which needs to be applied and further validated within the research community. In presenting the design theory, we follow the structure of IS design theories proposed by Jones and Gregor (2007). Jones and Gregor (2007) suggest that researchers describe a design theory along eight components: the *purpose and scope* of the design theory, the relevant *constructs*, the *principles of form and function*, the considered *artifact mutability*, *testable propositions*, underlying *justificatory knowledge*, detailing *principles of implementation*, and the description of *expository instantiations*. Our artifacts map to the design theory components as follows: The design objective and design requirements specify MSA systems' purpose and scope, clarifying what MSA systems need to accomplish. The abstract blueprint and design principles serve as the principles of form and function that describe MSA's general architecture and design. Complementary, the six design features, their ways of implementation, and the MSA archetypes prevailing in literature act as principles of implementation guiding the adaptation of the general MSA design to a design that fits the specific intended application precisely. Table 19 provides further details on the composition of the MSA design theory presented in this section.

Component	Description
Purpose and scope	MSA systems aim for the mobile assessment of an individuals' stress level based on data on the individual, their environment, and the individual-environment-interaction. The design is applicable for all intended applications and characteristics within the presented range of design requirements.
Justificatory knowledge	The design is based on well-established long-standing theories on stress in the social sciences – especially the Transactional Model of Stress by Gentry (1984) – that have previously been applied in IS research by other authors and on a body of research on stress sensing and affective computing in computer science and IS research.
Constructs	Core constructs for the design are 'stress', 'stressor', 'strain', and 'mobile stress assessment' (see the theoretical foundation of this section).
Principles of form and function	The abstract blueprint and the design principles guide MSA system designers in elaborating a design that satisfies the general design objective and design requirements. Consequently, we propose both elements to constitute the abstract functional design for MSA.
Principles of implementation	In contrast to the blueprint and design principles, the implementation of the design features is specific to the intended application of the MSA system. Thereby, the design features enable the adaptation of the general design to the specific intended application.
Expository instantiation	We presented five prototypes for different intended applications. The design of these systems implements the abstract blueprint, follows the proposed design principles, and tailors the design to the specific intended application using the design features. Based on this, we evaluated the design theory's effectiveness and utility.
Testable propositions	We claim that well-designed and implemented mobile systems following the design blueprint and principles presented here can assess an individual's stress level. In this section, we presented several instances that support this claim. Future research may further test this claim. Second, we claim that disregarding any single design principles or waiving any core component of the design blueprint will lead to a system that cannot assess an individual's stress level reasonably. This claim can be tested by developing alternative designs and instantiations and testing them against the objective and requirements. Note, however, that we do not claim that the list of design principles is complete. Based on the prior state of knowledge, we believe the scope, number, and level of detail of the design principles are helpful to advance the design knowledge. With further maturation towards a well-developed design theory, additional design principles will inevitably be proposed.
Artifact mutability	The solution domain – mobile devices and affective computing – is subject to constant and continuous change (Charlesworth 2009). The design enables a reaction to these changes. It is capable to include wearables and smartwatches as valuable data sources once they become widely distributed and accepted, or respond to future communication trends; for example., to include successors of WhatsApp and Facebook in terms of popularity. The design can also be transferred to new methods and models for data analysis and transformation.

Table 19: Compilation of an MSA Design Theory

Overall, the design theory presented here strongly builds on and combines extant design knowledge on MSA and is tested and expanded in own prototyping activities (Vom Brocke et al. 2020). It contributes to the literature on the topic of MSA by providing researchers and practitioners with extensive design knowledge on how to develop effective MSA systems (as a contribution to the design theory knowledge base in the Vom Brocke et al. (2020) framework) and by presenting five instantiations of MSA (contributing to the design entities knowledge base). Complementary, it contributes to DSR literature by providing an example of a theoretically grounded and empirically enhanced design theory that can inspire further researchers to strive for consolidated design knowledge in order to facilitate the development of effective IS.

Conclusion, Limitations, and Future Work

In this section, we responded to the call for the development of neuro-adaptive information systems (Riedl 2012; Vom Brocke et al. 2013) and composed a design theory for MSA based on extant design knowledge dispersed across the 136 MSA studies and new design knowledge resulting from the development of five MSA prototypes. This design theory builds on the findings from analyzing the literature that the basic architecture is similar across MSA instantiations. Overarching design principles should be followed in designing MSA systems. However, different intended applications of MSA require a targeted adaptation of the design features to the specific demands of the defined application. This design theory's design knowledge comprises and interrelates design requirements, an abstract blueprint, design principles, design features, and trade-offs between quality-focused design requirements and the design features. We presented the design theory along with the components of a design theory proposed by Jones and Gregor (2007). It is well-grounded in scientific literature and has been evaluated for its suitability and applicability for designing specific MSA systems and its effectiveness and utility in producing effective MSA instantiations sustained in real-world application (Venable et al. 2016).

Naturally, our work is subject to some limitations. First, although the design theory constitutes a meaningful contribution to literature as described in the previous section, some aspects of our work call for subsequent research to further test and extend our results. Although 136 studies are already a substantial amount, we did not yet search in all outlets of IS and adjacent disciplines, which might reveal additional insights into best practices in MSA design. Our literature analysis only considered papers published in 2010 or later but might have neglected very early works on MSA. The design knowledge presented in this work could be further refined by incorporating studies published before 2010 or in outlets that were not in our scope. Second, the trade-offs were derived from the insights during the development of five proto-types, although, we did not prototypically instantiate every single archetype. Furthermore, the range of possible uses of MSA is very broad and therefore our five prototypes can only address a small subset. nevertheless, these five prototypes have already provided valuable insights that can support future researchers and users in the design of MSAs. Third, stress is a multi-faceted phenomenon. In most prototypes, except for assessing stress based on pupil dilation, we focused on perceived stress, which is not identical to physiological stress (Riedl 2013). Thus, the design's evaluation of physiological stress measurements instead of perceived stress would be a valuable addition to the present research. Finally, future work should link stress assessment with stress management interventions, e.g., in the context of stress-sensitive information systems (Adam et al. 2014, 2017; Friemel et al. 2018; Jimenez and Bregenzer 2018). However, it is by no means clear that a technological solution for stress assessment is the most appropriate solution because technology itself is a potential stressor (Lee et al. 2014). Nevertheless, we contend that it is worth exploring and evaluating how mobile sensing and assessment can support stress management.

6. Understanding the Perceived Misfit in Modern Socio-Technical Systems

The research activities presented in Chapters 3 and 4 regarding the reciprocal interaction between the technical and social components are based on technostress's theoretical foundation introduced more than ten years ago by Tarafdar et al. (2007). As shown in the course of this dissertation, the digital workplace has changed significantly compared to more than ten years ago. This not only refers to the fact that the interaction with and use of DTMs has changed considerably but even more that societal and individual expectations changed. Therefore, the last chapter of this dissertation puts the current concept of technostress to the test and tries to understand the impending misfit within a socio-technical system associated with ongoing digitalization.

Recent socio-technical developments caused by ongoing digitalization (e.g., artificial intelligence, robotic process automation, anthropomorphic systems) change the work environment and culture. This change is intensified by the COVID-19-pandemic due to an increasing number of remote working employees and an increasing number of virtual collaborations. Digital and smart workplace technologies facilitate business processes and provide efficient communication and collaboration tools, "increasing the productivity of the workforce in the information age" (Attaran et al. 2019, p. 1).

However, the use of digital technologies also has a downside: it may cause stress. For example, information flows across many different channels, frequent interruptions, or the boundaries between work and private life become blurred due to continuous reachability (Tarafdar et al. 2010). These demands may cause stress. This specific form of stress was identified already in the 80s when Brod (1982, 1984) coined the term "technostress" to speak about "the human cost of the computer revolution" (Brod 1982) and a "modern disease of adaptation caused by an inability to cope with new computer technologies in a healthy manner" (Brod 1984). However, the intensity of use and diversity of digital technologies and virtual collaboration forms in the business context have changed considerably since the 80s. The contemporary perspective of technostress was shaped more than two decades later by seminal papers like Tarafdar et al. (2007), Ragu-Nathan et al. (2008), and Ayyagari et al. (2011). The core-framework centers around a misfit of demands arising from digital technology use and a person's resources to cope with these demands. Beyond that, there is also a bright side of technostress, but in the following, we will focus on the dark side (Benlian 2020; Califf et al. 2020; Tarafdar et al. 2019).

A motivation to study technostress has always been the charge in IT use behavior. Tarafdar et al. (2007, p. 304) suggested that “given the proliferation of [digital technologies] in the workplace in recent years, there are a number of ways in which their use can create stress for people using them”. Likewise, Ayyagari et al. (2011, p. 831) stated that “[w]ith the proliferation and ubiquity of information and communication technologies, it is becoming imperative for individuals to constantly engage with these technologies in order to get work accomplished”. Almost another decade later, Fischer et al. (2019, p. 1822) argued that they "see no reason why this [socio-technical] development would have stopped". Tarafdar et al. (2019, p. 7) also argue that technostress is a “continually evolving phenomenon as new types of IS […] and their use persistently emerge and reveal novel aspects of it”. Accordingly, La Torre et al. (2019) stated that the definition of technostress has changed over time and also Tarafdar et al. (2019) acknowledged this dynamism through an update of their core-conceptualization of technostress by assigning new aspects to known technostress creators. This can be seen, for example, in a literature study on technostress conducted by Nisafani et al. (2020), which found indications for additional technostress creators, which, however, refer less to the technology itself but more to the handling of it and the expectations set by users (e.g., role ambiguity, flexibility). However, Fischer et al. (2019) remarked that it is disputable whether new aspects of technostress can simply be added to the existing framework of technostress creators or whether additional dimensions are needed. This raises the question of whether the concept of “technostress” is still up to date and suits the prevailing circumstances, with digital technologies having reached an unprecedented variety, pervasiveness, and usage intensity in all domains of life.

Contemporary research in the field of technostress deals with topics such as stress appraisal (e.g., Benlian (2020), Califf et al. (2020)), stress coping (e.g., Tarafdar et al. (2020), Pirkkalainen et al. (2019)), stress outcomes (e.g., Chen et al. (2019), (La Torre et al. 2020)), and the design of stress-sensitive systems (e.g., Adam et al. (2017), Jimenez and Bregenzer (2018)). This is equally valuable and important and should not be neglected since it is the appraisal of technostress creators and the application of coping measures that determine the extent to which employees experience technostress at all. At the same time, however, it is also crucial to regularly take a look “back” and examine the extent to which the working life has changed and how this change affects technostress creators, their perception by employees, and the appropriate prevention and coping measures.

Hence, a conceptualization of stress from digital technology use that fits the new socio-technical context of digital work is important to understand the resulting psychological strain and its consequences (e.g., low productivity, dissatisfaction at work, health issues) and to allow researchers and practitioners to design and analyze measures countering this dark side of digital transformation. We do not suggest the need for an entirely new theory of technostress. However, as context matters for theories (Hong et al. 2014) and as in light of digital transformation (Vial 2019), the technological, organizational, and social context of work changed for many. We believe the time has come for an update of technostress theory. In this, we adopt a cumulative knowledge perspective.

Therefore, we pose the following research questions:

RQ1) Which demands from contemporary work practices relating to digital technologies cause stress for employees?

RQ2) How do the different demands relate to each other?

To answer these research questions, we applied a sequential qualitative-quantitative mixed-methods research design and followed the guidelines by Venkatesh et al. (2013) and Venkatesh et al. (2016). Our research is divided into a qualitative phase grounding our research in a general conceptual framework relying on multiple expert interviews and group discussions, followed by a quantitative phase analyzing survey data from overall 5,005 employees.

Key results are as follows: Based on theoretical reasoning and empirical data, we present a holistic framework of 12 contemporary demands from work practices relating to digital technology use. This includes nine demands known as technostress creators in the extant literature and three newly identified demands. Our data suggest a hierarchical structure with four second-order factors underlying the demands. Further, we present a valid and reliable survey-based measurement model for the demands. Next, we embed the hierarchical model of demands from digital work in a nomological net showing the work and health-related effects. Finally, given the magnitude of change regarding the considered stress creators and the context of digital transformation – we suggest the concept of “digital stress” as an update and extension of technostress.

This chapter is structured as follows: the first subsection describes the conceptual foundation and current state of knowledge in the literature. Following this, our mixed-methods research process and related design decisions are explained. We then present the qualitative phase of our research and focus on the conceptual development of the phenomenon of stress induced by digital technologies. After that, we jump into the quantitative phase of our research and presents the survey results. The subsequent subsection discusses the results of the different phases and the meta-inferences before the last subsection concludes.

Conceptual Foundation

Brod (1984, p. 16) describes technostress as “a modern disease of adaptation caused by an inability to cope with the new computer technologies in a healthy manner”, illuminating the phenomenon from an early perspective. The scholarly concept from Tarafdar et al. (2007, p. 304) in contrast focuses on the workplace, stating that “[i]n the organizational context, technostress is caused by individuals' attempts and struggles to deal with constantly evolving [information and communication technologies] and the changing physical, social, and cognitive requirements related to their use”.

The definitions stem from different decades and contexts, but they have something in common: They are based on the transactional theory of stress. According to this theory, stress is more than a threatening, potentially harmful event and more than the reaction an individual shows to a stressor. Otherwise, every person in a demanding situation would show the same "stress". Stress is neither anchored solely in the environment nor in the person. It is created in a transactional process (Lazarus and Folkman 1984). It means that demands are transmitted from the environment to a person while being appraised. Appraisal signifies the validation of situational facets, “with respect to the significance for well-being” (Lazarus and Folkman 1984, p. 31), together with the individual resources and possibility to handle this situation. Following Lazarus and Folkman (1984), technostress arises when negative consequences resulting from digital technology use are anticipated and an imbalance between these demands, and the user's personal or organizational resources (Tarafdar et al. 2007) to meet the demands, occurs. It is important to note that digital technologies exist in various forms and refer to information, computing, communication, and connectivity technologies (Vial 2019).

In their recent literature analysis of existing work on technostress, Tarafdar et al. (2019) structured existing research on technostress along with a framework that builds on the transactional process. This framework includes technology environmental conditions, technostress creators, consequences, and moderators of the technostress creators and outcomes relationship.

Technostress creators are specific demanding conditions that occur during IT use, which have to be met using personal resources. Research has identified several technostress creators, such as techno-invasion, techno-overload, techno-complexity, techno-uncertainty, techno-insecurity

(Ragu-Nathan et al. 2008; Tarafdar et al. 2007). Techno-invasion refers to situations that require being constantly reachable and connected, which may cause the boundary between work and private life to blur. Techno-overload is associated with situations in which digital technologies induce a greater workload and higher speed of work. Techno-complexity describes situations where digital technologies make users feel that they do not have the needed skills and experiences to deal with digital technologies' complexity and are forced to spend time and effort learning it. Techno-uncertainty refers to situations where digital technologies are frequently changed and upgraded and require users to develop their abilities and knowledge continually. Techno-insecurity describes situations where the threat of losing one's jobs due to automation or missing skills to deal with digital technologies is perceived by users.

The five well-established technostress creators brought up by Tarafdar et al. (2007) and Ragu-Nathan et al. (2008) attracted since their introduction much attention in research on technostress. However, other aspects discussed in the literature can create technostress and relate to negative consequences for individuals using technologies at the workplace. Adam et al. (2017) discuss techno-unreliability. This technology-related stressor comprises system malfunctions as well as IT hassles. Galluch et al. (2015) focus on digital-technology-enabled interruptions, such as emails or instant messages. Ayyagari et al. (2011) consider role ambiguity and invasion of privacy as part of the technostress concept. The former describes the unpredictable consequences of the conflict between performing a role and lacking information for doing this adequately. For example, this might occur when an employee is unsure whether to prioritize dealing with digital-technology-problems or work activities. The latter involves the perceived impairment of one's privacy. This one is not to be confused with techno-invasion. While techno-invasion focuses on the blurring boundaries between work and private life, invasion of privacy refers to the perception that the private and occupational use of digital media during work time can easily be traced, and the employer may invade privacy.

The consequences of technostress have been analyzed in numerous studies. The most mentioned consequence is the negative effect on end-user satisfaction, followed by job satisfaction, performance, productivity, and organizational commitment (Sarabadani et al. 2018). Tarafdar et al. (2007) stated that higher technostress results in lower productivity. Ragu-Nathan et al. (2008) showed that technostress creators decrease job satisfaction and organizational and continuance commitment. Both are emphasized by Tu et al. (2005), who found higher employee turnover can result from technostress next to lower productivity. Concerning individuals' health, Mahapatra and Pati (2018a) found that, in an Indian context, techno-invasion and techno-insecurity can lead to burnout, which, in turn, is associated with several negative outcomes on the organizational and individual level, including lower productivity, job satisfaction, and higher absenteeism as well as depression and anxiety (Maslach et al. 2001). For German employees, Gimpel et al. (2018b) found that higher levels of technostress go along with a higher number of people reporting to suffer from headaches, fatigue, sleeping problems, and exhaustion, for example.

Factors moderating the relationship between technostress creators and outcome involve individual resources of the employees, such as technology self-efficacy, technology competence, control over access to task-related information, or personality traits (e.g., neuroticism, agreeableness, and extraversion) (Tarafdar et al. 2019). A current overview of antecedents, causes, inhibitors, and consequences of technostress can be found in Nisafani et al. (2020).

Research Process

In our research process, we follow a mixed-methods design. Mixed-methods research designs "contain elements of both quantitative and qualitative approaches" (Tashakkori and Teddlie 1998b, p. 5). Within the IS discipline, mixed-methods designs are beneficial since context changes frequently. Researchers often have difficulty drawing significant insights from existing theories and perspectives (Venkatesh et al. 2013). Mixed-methods designs offer three specific benefits: the ability to "address confirmatory and explanatory research questions", to "provide stronger inferences than a single method or worldview", and to "produce a greater assortment of divergent and/or complementary views" (Venkatesh et al. 2016, p. 437). Given the general multiplicity of studies on technostress and the changed context, a mixed-methods design is well suited to our work.

Our study's mixed-methods design began by articulating two research questions. We follow a developmental purpose whereby we conduct a qualitative study first and use the results from this strand to develop the research model tested in the second strand of research (Tashakkori and Teddlie 1998b; Venkatesh et al. 2013; Venkatesh et al. 2016). We adopt multiple paradigms as our epistemological stance. During the qualitative phase (Phase 1), we take an interpretive perspective. During the quantitative phase (Phase 2), we adopt a positivist approach. The methodology can be classified as "mixed-methods multistrand" (Venkatesh et al. 2016, p. 443), whereby both strands are equally important. We use a sequential sampling strategy with parallel samples and perform data analysis sequentially to help build the research model for the quantitative study from the results of the qualitative phase (Venkatesh et al. 2016). In Appendix F.1 and Appendix F.2, we elaborate on our choices and research questions that guided the mixed-methods design and articulate how we follow established criteria for mixed-methods designs.

Overall, the mixed-methods design (Figure 20) is divided into two phases and influenced by contextual research studies (see Hong et al. 2013). In Phase 1, we accomplish the following: (1a) We ground our research in a general conceptual framework and compile known demands of digital work discussed in current literature. This provides a holistic view of stress and technostress. (1b) Subsequently, we reveal new demands from digital work through interviews with experts from different fields and focus group discussions. By identifying the currently most important/significant stressful aspects of the interaction with digital technologies, we understand the conditions that may give rise to a technostress creator. We conclude with qualitative inferences by analyzing the interview data and iteratively reviewing the literature base. The demands are defined, and the concept of technostress is evaluated to understand whether it complies in its current form with the (newly) defined technostress creators (Hargrove et al. 2013). In Phase 2, we accomplish the following: (2a) We operationalize the constructs and pretest our measurement model. Therefore, we develop items for newly identified demands that emerged from the qualitative study and translate existing scales. The associated measurement models are examined. (2b) Next, we validate our measurement model and by this the findings from the qualitative strand by enriching it with findings from an online survey answered by a representative sample from the German workforce. This provides a validated measurement instrument to assess the new demands of digital work. Lastly, we reveal higher-order structures to understand the multi-level structure of the demands (2c) We select the best structure for the demands based on another online survey and embed the concept in a nomological net to test validity. This provides the foundation for theory development. We conclude our mixed-methods study by integrating the findings from the qualitative and quantitative phase, drawing meta-inferences that guide our theory development in the contribution.

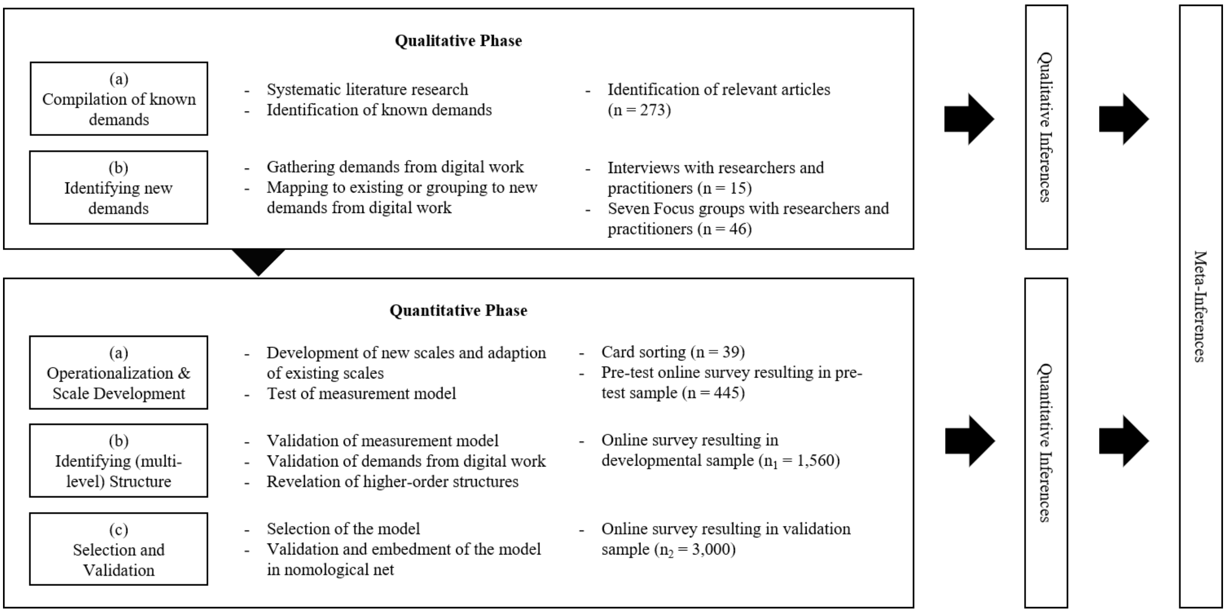


Figure 20: Research Process of the Mixed-Methods Research Paradigm

Qualitative Phase

In the literature that builds our research foundation, we aimed to identify phenomena classified as technostress creators. We searched in various international databases: EBSCO Business Source Premier, EBSCO Academic Search Premier, EBSCO Psych, Web of Science, and PubMed. Since the seminal paper by Tarafdar et al. (2007) was published in 2007, only publications from this year onwards were included. Types of publications that were considered are academic journals, conferences, proceedings, books, book chapters, and dissertations. In a first step, we developed several search strings for aspects, which might be linked to technostress. These were technologies (e.g., digital device, laptop, notebook, wearables, mobiles, crowd workers, robots), workplaces (e.g., mobile work, work-related, employee), as well as different possible outcomes such as stress and strain (e.g., exhaustion, well-being), detachment (use behavior, work-life conflict), monitoring (e.g., monitoring, surveillance), cognition (e.g., problem-solving, decision making), acceptance (satisfaction, willingness), and job (e.g., performance, productivity). Besides, we used a string for excluding specific topics like electromagnetics, animals, or children. In a second step, we combined search strings for technology, workplaces, excluding topics with one specific outcome at a time. Overall, 273 articles were identified based on their abstract to be relevant because they were directly linked to technological-induced stress within working time. The final list covered a broad picture of literature in several areas. For these, we extracted the used operationalization of technological-induced stress. Here, we focused on whether technological-induced stress was seen as a first-order or second-order construct with different underlying facets. If the last was the case, we further checked if those used facets went beyond the five technostress creators introduced by Tarafdar et al. (2007). This led to the nine technostress creators that we covered in the Conceptual Foundation section.

Identifying New Technostress Creators

Besides these established technostress creators unfolded by the literature research, we collected qualitative data from expert interviews and focus groups to gather information about potential new technostress creators to extend the technostress concept. Both interviews and focus groups are commonly used for in-depth analysis instead of generalizing to a population. While interviews are often conducted with participants from whom you hope to learn how experiences or knowledge work, focus groups are more appropriate for research questions of how certain issues are talked about or debated (Secor 2010). In this regard, we conducted expert interviews and one expert focus group to get insights from a broader and more general practical perspective. Employee focus groups were conducted to receive information from employees affected by technostress in their everyday working life.

Interviewees for expert interviews were chosen both from science and practice to cover a variety of perspectives. Instead of defining a total number of interviews upfront, theoretical saturation from grounded theory was used as a termination criterion (Corbin and Strauss 2014). Therefore, interviews were conducted until there was no additional insight. In total, 15 semi-structured interviews were realized with experts´ backgrounds ranging from employer and employee representative, corporate health management, moral ethics, occupational science, computer science, and human resources. Table 20 shows a list of all interviewed experts. All interviews were transcribed and analyzed.

Code	Role
Exp1	Chairman of the works council for a manufacturer of entertainment and communication technology with over 2,000 employees
Exp2	Employee of the human resources department for a manufacturer of entertainment and communication technology with over 2,000 employees
Exp3	Head of human resources department for SME focusing on customer acquisition and retention
Exp4	Person in charge of occupational reintegration management for SME focusing on customer acquisition and retention
Exp5	Chairman of the works council for a SME focusing on customer acquisition and retention
Exp6	Scientific director for a federal institute focusing on occupational safety and health
Exp7	Research Associate with a focus in working-time and work organization for a federal institute focusing on occupational safety and health
Exp8	Professor for moral theology for a German university
Exp9	Employer representative working for the employers' association for the largest and strongest industry in the country
Exp10	Former vice-chairman of the works council and lecturer for a training institute for works councils
Exp11	Professor for sociology for a German university
Exp12	Software developer for a university IT department
Exp13	Head of competence field occupational safety for an occupational health management service provider responsible for over 1 Mio. employees
Exp14	Regional director for an occupational health management service provider responsible for over one Mio. employees
Exp15	Regional director for an occupational health management service provider responsible for over one Mio. employees

Table 20: List of Experts and their Function

The expert focus group consisted of researchers from computer science, information systems, and psychology. The employee focus groups consisted of different occupational groups. However, there were separate groups for executive staff and employees. In total, seven employee focus groups and two focus groups with research experts were conducted with five to eight participants. An overview of all focus groups can be found in Table 21. In total, 61 individuals took part in the qualitative data collection, 15 in individual interviews and 46 in focus groups.

Focus group	Number of participants	Level of hierarchy	Occupational group	Age	Sex
1	6	Staff	Controlling, human resource, marketing, product manager	31 – 50	Male: 4 Female: 2
2	8	Staff	IT support, account manager, media designer/production, business development, tourism	27 – 49	Male: 5 Female: 3
3	7	Staff	Counseling, psychologist, doctors, distribution	32 – 47	Male: 1 Female: 6
4	5	Executive Staff	Distribution, IT	39 – 56	Male: 4 Female: 1
5	6	Department Managers	IT, marketing, quality management, finance, supply chain management	37 – 55	Male: 4 Female: 1
6	6	Researchers	Research experts in information systems	25 – 28	Male: 4 Female: 2
7	8	Researchers	Research experts	38 – 64	Male: 5 Female: 3

Table 21: Overview of the Participants from the Focus Groups

The basic structure of both the expert interviews and focus groups was similar: first, the interviewee, respectively, the participants were asked about their currently used technologies. Here, we deliberately avoided the term technostress to ask for a general experience in handling digital technologies. Afterward, they had to name potential creators of stress caused by the technologies and the resulting consequences for employees. In the end, coping strategies, as well as necessary resources to prevent technostress, were discussed. The full interview guideline is available in Appendix A.2 and the guideline for the focus groups is in Appendix A.3.

We used a qualitative deductive approach for analyzing expert interviews (Pearse 2019). At first, we developed a codebook based on our previously conducted literature review. For the nine technostress creators from literature, we created codes for sources of the respective technostress-creators, consequences resulting from these sources, coping behaviors as well as resources for preventing technostress derived from the specific technostress-creator. Furthermore, we subdivided the codes for sources and resources into technological, organizational, and individual types of origin. Consequences were divided into the sections physiological, cognitive, and behavioral, whereas coping strategies were divided into problem-based and emotion-based. Besides, a general code with the same sub codes mentioned above was created for topics not concerning one of the literature's technostress-creators. The codebook was then applied to the analysis of the collected data to identify themes. Those can be described as patterns within the data (Braun and Clarke 2006). These themes can derive from codes, which either were existing within the original codebook or were added afterward within the analysis process (Pearse 2019). Our primary focus was on those themes that could not be linked to one of the most relevant technostress creators to identify potentially new creators.

A moderator and an assistant ran the focus groups and they recorded the most important results from the discussions. These notes were also coded and analyzed. We talked about possible newly detected technostress creators derived from the expert interviews in detail during these focus group discussions. From now on, we present results from this qualitative strand illustrated with quotes from the expert interviews.

Overall, we found three themes reoccurring within several of the conducted interviews and focus groups that could not be linked to established technostress creators. The first theme emphasizes the potential monitoring of employees due to new arising digital technologies. In this regard, one expert and member of a work council (Exp1) said:

"*To some degree, our production line is close to industry 4.0. For almost 20 years now, we record and process data. That´s why we can assign which employee on any given day in the past produced a device if, for example, a client complains about a defective one. For us, this is absolute monitoring of employees. In this regard, employees have to be protected so that the new possibilities won´t lead to surveillance. This is a common topic for us. Once employers have the possibility to monitor employees even a little bit, we try to prevent them from doing so. And most of the new technologies can easily be used for monitoring employees*."

However, monitoring cannot only lead to blame employees for possible mistakes made in the past. In addition, new technologies offer possibilities to compare performances among employees. One employee representative (Exp10) explained:

"*Regarding digital stress, one common question is related to new possibilities of monitoring. A lot of new technologies and forms of work, like, for example, working in a cloud or crowd, offer new possibilities of usability, interpretability, and comparability. A one-sided transparency, as I call it. This doesn´t even have to be strict efficiency control. However, one does become more visible. This is an important point*."

The second theme, which was reoccurring and not related to the technostress creators identified in literature, emphasizes a certain non-availability of modern technologies. In this regard, one expert, a scientific director (Exp6), mentioned:

"*Otherwise, one can name a restrictive use of access rights as well as a more general access to technologies. That one cannot work as one wants to or the situation requires because of organizational regulations*."

These situations, in which one knows that technologies might facilitate one's work, but one is not allowed to use them, can lead to perceived stress. One expert, a professor for moral theology (Exp8), summarized these situations as follows:

"*I notice a tendency towards anachronism. From my perspective as a professor, I have to correct exams and write reports handwritten. You ask yourself: 'which year are we living in?' So much additional effort just because you are not allowed to work with digital technologies. This definitely leads to stress. This is ridiculous. As a workaround, I write everything with my computer, print my comments as etiquettes and glue these into the exams. Until now, no one did complain about it. In some domains, especially if regulated by the state, you have to work in ways, which do not fit in our modern times. This waste of time causes stress*."

Participants in focus groups also mentioned this theme. While asked for potential creators of stress, most participants mentioned inadequate software design, own insufficient competence, or unreliability of used technologies as most occurring stress-creators caused by technologies. These themes are common within technostress literature. However, few participants in different focus groups mentioned a lack of access rights and the non-availability of necessary technologies as a stress source.

The third theme that occurred was a lacking sense of achievement of employees when working with digital technologies. This phenomenon was mentioned in the seventh focus group when discussing potential creators of stress. In the discussion, one of the attendees – a professor for computer science – mentioned lacking a sense of progress or achievement and described it as a feeling of not seeing results of one's work with digital technologies – other than seeing physical results when working as a craftsperson. According to the attendee, it was a problem that he experienced himself and that in his research, he was concerned with the design of technologies that address this problem. After some discussion about this, the focus group concluded by suggesting a lacking sense of achievement to be another digital work demand as the ones already mentioned in the literature.

Defining Twelve Demands from Digital Work

Technostress literature refers to the stress that is created by interacting with digital technologies as technostress creators or techno-stressors (Tarafdar et al. 2007; Tarafdar et al. 2019). However, strictly speaking, one has to use the term potential technostress creators or potential techno-stressors because if these circumstances lead to stress depends on the individual and its appraisal. Therefore, the attribution if, for example, an unreliable technology is a technostress creator, is a result and as such part of the analysis instead of a conceptual foundation. Benlian (2020) already diverges from the established term and "calls for contextualizing general theories in IS research […]" (Benlian 2020, p. 1263). He uses the term "technology-driven work stressors" to emphasize "the socio-technical nature of ICT that essentially and distinctly shapes the frequency, valence, and intensity of the stress experienced at work" (Benlian 2020, p. 1263). At the same time, however, he uses this term without explicitly introducing it. The term is focused on the technology itself, just like the contemporary term technostress creator. Therefore, we decide, similar to Benlian (2020), to borrow from general psychology (Lazarus and Folkman 1984), work psychology (Bakker and Demerouti 2007), and management literature (Kirmeyer 1988) and use the "demand" wording that already appears in Tarafdar et al. (2007), Ragu-Nathan et al. (2008), Ayyagari et al. (2011), and Bakker and Demerouti (2007). Thus, we use the term demands from digital work as a broader term to comprise the possibility that, for example, an unreliable technology might not be appraised as threatening by individuals.

Summarizing the results from the literature review, expert interviews, and focus groups, we define twelve different digital work demands. On the one hand, these are uncertainty, insecurity, complexity, invasion, overload derived from the technostress concept by Tarafdar et al. (2007). On the other hand, these are supplemented by the above mentioned and explained aspects of unreliability introduced by Fischer and Riedl (2015) and Adam et al. (2017), role ambiguity and invasion of privacy taken from Ayyagari et al. (2011), as well as interruptions from Galluch et al. (2015). The latter aspects are already used sporadically and separately in technostress literature, but all together have not yet been included in an overall construct of technostress. Furthermore, by conducting expert interviews and focus groups, we identified three new digital work demands, which have not yet been covered by hitherto existing dimensions of technostress: performance control, non-availability, and lacking sense of achievement. Performance control is the perception that one is constantly monitored and assessed. This is mainly because of modern technology, enabling increasing possibilities in collecting data and comparing performance data among employees. Non-availability is the perceived conflict between knowing how to fix problems or facilitate work processes by using new technology and not being able to do so because of organizational restrictions. Lacking sense of achievement is the perception of not having made significant progress during working hours. This is mainly because employees can hardly assess work already done because of its digital and non-physical nature. Table 22 summarizes all twelve demand from digital work and their definitions.

Construct	**Definition**
Invasion	Invasion “describes the invasive effect of [digital technologies] in terms of creating situations where users can potentially be reached anytime, employees feel the need to be constantly ‘connected,’ and there is a blurring between work-related and personal contexts.” (Tarafdar et al. 2007, p. 311)
Overload	Overload “describes situations where [digital technologies] force users to work faster and longer.” (Tarafdar et al. 2007, p. 311)
Complexity	Complexity “describes situations where the complexity associated with [digital technologies] makes users feel inadequate as far as their skills are concerned and force them to spend time and effort in learning and understanding various aspects of [digital technologies].” (Tarafdar et al. 2007, p. 311)
Insecurity	Insecurity “is associated with situations where users feel threatened about losing their jobs as a result of new [digital technologies] replacing them, or to other people who have a better understanding of the [digital technologies].” (Tarafdar et al. 2007, p. 311)
Uncertainty	Uncertainty “refers to contexts where continuing changes and upgrades in an [digital technology] unsettle users and create uncertainty for them, in that they have to constantly learn and educate themselves about the new [digital technologies].” (Tarafdar et al. 2007, p. 311)
Unreliability	Unreliability describes situations in which individuals “face system malfunctions and other IT-hassles” (Fischer and Riedl 2015, p. 1462).
Role Ambiguity	Role ambiguity is associated with situations where “there is uncertainty as to whether an individual should expend his or her resources to perform the task requirements at work or to acquire new skills.” (Ayyagari et al. 2011, p. 842).
Invasion of Privacy	Invasion of privacy refers to situations in which individuals “are becoming increasingly concerned that their privacy could be invaded by [digital technologies].” (Ayyagari et al. (2011, p. 841) based on Best et al. (2006))
Interruptions	Interruptions describe situations where an individual´s attention is shifted away from a current task by an external, digital-technology-based source (Galluch et al. 2015).
Performance Control	Performance control describes situations where users of digital technologies feel that technologies are used to monitor and assess their performance.
Non-Availability	Non-availability refers to situations where an individual is impaired in their activities because technologies, which might facilitate work processes, are unavailable due to organizational restrictions, safety, or monetary reasons.
Lacking Sense of Achievement	Lacking sense of achievement refers to situations where a user of digital technologies feels that they hardly make work progress as completed tasks with digital technologies can be assessed poorly due to their digital, non-physical nature.

Table 22: Definition of the Twelve Demands from Digital Work

This concept of twelve demands from digital work resulting from qualitative investigations needs to be put to the test. Accordingly, in phase 2 of our mixed methods research, multiple quantitative studies were conducted with the superordinate goal to test the insights generated in the first, qualitative strand of research.

Quantitative Phase

The quantitative strand assesses the identified twelve demands from digital work from a positivist perspective. Specifically, we use cross-sectional survey data to test convergent, discriminant, and nomological validity. Along the way, we develop and validate a measurement instrument for the demands from digital work and identify a higher-order structure among these demands. A fundamental principle for understanding constructs and building theory in research is the nomological net. CRONBACH and MEEHL (1955, p. 294) state that "scientifically speaking, to make clear what something is" means to set forth the laws in which it occurs. We shall refer to the interlocking system of laws that constitute a theory as a nomological network". This is done by embedding the construct of interest – in this case, the identified twelve demands from digital work – in a nomological net with theoretically related entities and empirically test these relationships.

Developing the Measurement Model

For the quantitative investigation, it is essential to have a measurement instrument to assess the latent non-observable variables of interest. The starting point was the findings and aggregated insights from the first strand of the mixed methods research: Twelve different aspects resulting from digital technology use, prone to create stress and their respective definitions. For some of these aspects, scales already exist. In contrast, measurement instruments had to be developed from scratch for the newly revealed aspects (e.g., non-availability, performance control, and lacking sense of achievement). Therefore, we follow the guidelines for developing and evaluating measurement instruments by Hinkin (1998) and MacKenzie and Podsakoff (2011). We give an overview of the steps suggested by MacKenzie and Podsakoff (2011) here and provide the details in Appendix F.3.

Step 1: *Develop a conceptual definition of the construct*. This step has been covered in Phase 1 of our mixed-methods study. The qualitative investigations concluded with a definition of twelve demands from digital work, as presented in Table 22.

Step 2: *Generate items to represent the construct*. We used the validated measurement instruments from Ragu-Nathan et al. (2008) for overload, invasion, complexity, insecurity, and uncertainty, from Ayyagari et al. (2011) for role ambiguity and invasion of privacy, and Galluch et al. (2015) for interruptions. For the newly identified demands, non-availability, performance control, and lacking sense of achievement, we developed six items each based on the definitions of these constructs (Table 22) considering standard guidelines (Hinkin 1998; MacKenzie and Podsakoff 2011; Podsakoff et al. 2003).

Step 3: *Assess the content validity of the items*. We performed a card-sorting with 39 participants and revised the wording of the newly developed items where necessary.

Step 4: *Formally specify the measurement model*. We specify the measurement model as first-order reflective for each of the established scales as suggested by Ragu-Nathan et al. (2008) and likewise for the newly developed scales. Furthermore, we allow for correlation among the twelve demands. In a later step, we will investigate whether there are higher-order structures among the twelve demands.

Step 5 & 6: *Collect data to conduct pre-test & scale purification and refinement*. We ran a pre-test with 445 participants in an online-survey and performed an EFA. For non-availability and lacking sense of achievement, the EFA revealed a lack of convergent validity triggering a re-wording of some items.

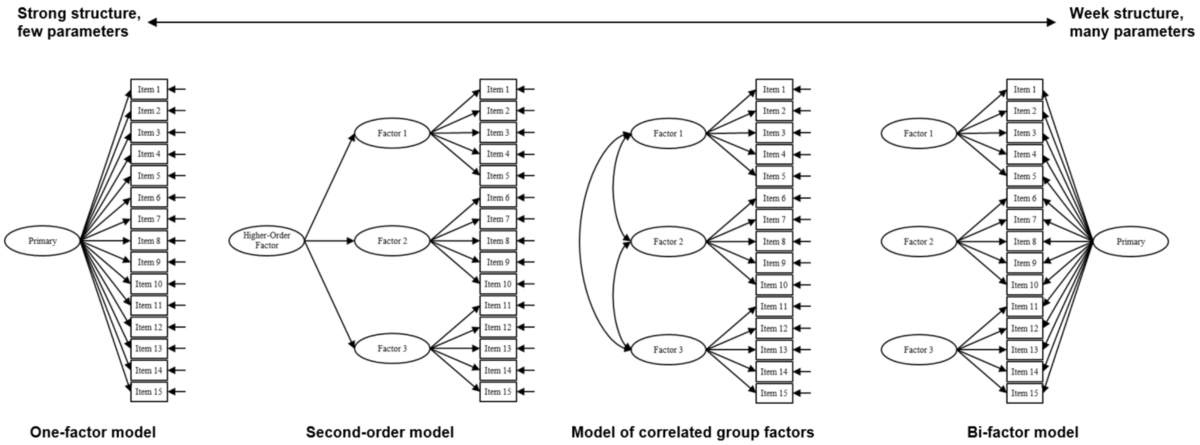
Step 7 & 8: *Gather data from new sample and reexamine scale properties*. Using the revised scales, we collect a new data set from 1,560 respondents participating in an online survey (developmental sample). A CFA showed a good fit and, this time, likewise, did the discriminant and convergent validity. Besides, Cronbach’s Alpha showed satisfactory values for the twelve demand from digital work.

Overall, these steps 1 to 8 suggested by MacKenzie and Podsakoff (2011) led us to a validated measurement instrument for all twelve demands from the digital work. Details on these steps are provided in Appendix F.3. The final scale is in Appendix F.4. MacKenzie (2011) also mentions in step 8 that it should also be examined to what extent a multidimensional structure is present, as we already pointed out in our fourth step. We defer steps 8 and 9 to the following sub-sections, where we first use the developmental sample (n_1 = 1,560) to investigate the structure of the twelve demands. Next, we gather new data for the validation sample (n_2 = 3,000) to re-assess scale validity, select among the potential structures of the demands, and embed the final structure in a nomological net. We omit step 10, as it is not relevant for our research questions.

Finding Higher-Order Structures

The high number of demands from digital work suggests that they are not all completely unrelated, but that they also have a certain relationship. For example, short-term demands such as interruptions and reliability could be grouped as well as insecurity and uncertainty as long-term chronic demands. Similarly, invasion of privacy and performance control have in common that both demands involve collecting or accessing personal data by third parties – the first focusing on the private life and the second focusing on the working life. Thus, on theoretical grounds, there is no reason to believe that the demands are unrelated (that is why we used oblique rotation in the EFA for developing the measurement model). Even stronger, the above reasoning suggests that there might be a higher-order-structure. Knowing such structures is desirable as it makes for a stronger theory. Weber (2012) discusses a trade-off between parsimony and theory's predictive and/or explanatory power and recommends, concerning the work of Miller (1956), that there should be no more than seven constructs to reduce complexity to a manageable level. Accordingly, we aim to describe our 12 demands from digital work by a few higher-order factors that are easier to memorize.

In general, there are four different models for a structure (Rindskopf and Rose 1988). Figure 24 displays them illustratively for three factors and five items rather than the twelve factors and three to five items we have. From prior literature (e.g., Tarafdar et al. (2007), Ragu-Nathan et al. (2008), Ayyagari et al. (2011)) and our parallel and MAP analyses in the development of the measurement model, we know that the structure of demands from digital work is different from the one-factor model. Prior research such as Tarafdar et al. (2007) and Ragu-Nathan et al. (2008) assumes a model with one reflective second-order construct comprising technostress creators while Ayyagari et al. (2011) assume a model of freely correlated group factors. Given the high number of now twelve demands from digital work, the question arises whether such correlated group factors are most appropriate or whether a second-order model or a bi-factor model is a better fit. Until now, we know the structure of twelve correlated group factors. Hence, we next empirically build the best-fitting second-order model and bi-factor model on the developmental sample (n_1 = 1,560) and then, in turn, use the validation sample (n_2 = 3,000) to select the best model on new data.



Notes: Circles represent latent factors, squares represent manifest variables

Figure 21: Possible Models based on Rindskopf and Rose (1988)

First, the data from the developmental sample suggests a potential second-order structure. A reason for this is when we correlate the latent factors representing the twelve demands in an EFA with oblique rotation on the data from the developmental sample, unexpectedly high correlations (Table 23) up to 0.75 are observable.

Construct	INV	OVE	CO	INS	UNC	UNR	ROL	IOP	INT	PER	NON	LSA
INV	1											
OVE	0.65	1										
CO	0.63	0.66	1									
INS	0.73	0.72	0.66	1								
UNC	0.48	0.56	0.43	0.64	1							
UNR	0.48	0.62	0.51	0.51	0.43	1						
ROL	0.65	0.69	0.75	0.68	0.44	0.58	1					
IOP	0.42	0.49	0.43	0.41	0.27	0.44	0.54	1				
INT	0.57	0.71	0.61	0.57	0.42	0.62	0.70	0.54	1			
PER	0.40	0.59	0.45	0.50	0.38	0.45	0.55	0.67	0.55	1		
NON	0.59	0.54	0.59	0.55	0.34	0.52	0.66	0.44	0.58	0.42	1	
LSA	0.64	0.62	0.67	0.64	0.41	0.48	0.75	0.47	0.65	0.43	0.64	1

Notes: INV = Invasion, OVE = Overload, COM = Complexity, INS = Insecurity, UNR = Unreliability, ROL = Role Ambiguity, IOP = Invasion of Privacy, INT = Interruptions, PER = Performance Control, NON = Non-Availability, LSA = Lacking Sense of Achievement

Table 23: Correlations between the Demands from Digital Work (n_1 = 1,560)

Multilevel exploratory factor analysis run on the developmental sample reveals a possible higher-order structure (Navruz et al. 2015). In the first step, an EFA with twelve predefined factors was applied. The correlations of the factor score estimates were extracted and used as input to run another EFA (principal axis factoring with oblique rotation). Parallel analysis suggests four or five factors; for the fifth factor, the eigenvalue comparison between actual and simulated data shows only a marginal difference. Thus, we extracted five factors in an EFA similar to before and inspected the loadings. For the fifth factor, the maximum loading of any of the first-order factors was 0.37, below the conventional threshold of 0.4 to consider it a major loading. Hence, we decided to drop the fifth factor and extracted four factors in an EFA with oblique rotation (Table 24).

	Factor 1	Factor 2	Factor 3	Factor 4
Complexity	0.51			
Invasion	0.41			
Non-Availability	0.51			
Lacking Sense of Achievement	0.79			
Role Ambiguity	0.75			
Interruptions		0.41		
Overload		0.56		
Unreliability		0.46		
Insecurity			0.83	
Uncertainty			0.56	
Invasion of Privacy				0.88
Performance Control				0.69

Notes: Loadings < 0.4 are not displayed

Table 24: Factor Loadings for 4 Second-Order Factors

This resulted in a desirable loading matrix with each first-order factor loading highly on exactly one second-order factor (loadings ranging from 0.413 to 0.884 all exceeding the 0.4 threshold), no major cross-loading (maximum is 0.36), and each second-order factor being relevant in the sense of having at least one first-order factor loading highly on it. Table 25 provides names, definitions, and explanations for the four higher-order demands from digital work.

Construct	Definition	Explanation
Impediment	Impediment describes the demands from digital work from complexity, invasion, non-availability, lack of sense of achievement, and role ambiguity.	During a workday, different activities must be carried out to achieve the objectives associated with the work role. However, the (steady) presence or absence of digital technologies may contribute to the perception that making progress in achieving objectives is more complicated.
Interference	Interference describes the demands from digital work arising from interruptions, overload, and unreliability.	Digital technologies aim to support the handling of tasks in everyday work by facilitating communication and collaboration with others and accomplishing activities. However, digital technologies can also foster the perception that tasks' execution is prolonged due to incidents occurring during the direct interaction with the technologies or interferences caused by third parties using technologies.
Constant Change	Constant change describes the demands from digital work arising from insecurity and uncertainty.	Constant change and new digital technologies lead to higher demands of building up the necessary skills and abilities to carry out work-related tasks or cause job requirements not to be fulfilled due to incorrect or inefficient use of digital technologies.
Exposure	Exposure describes the demands from digital work from invasion of privacy and performance control, invasion, non-availability, lack of sense of achievement, and role ambiguity.	The use of digital technologies (unknowingly to the user) leaves digital footprints with varying visibility. Furthermore, the increasing use of connected digital technologies enables easier access and simplified processing of these data and may foster the perception that information about persons from different contexts and sources is provided to third parties.

Table 25: Explanation, Definition, and Interpretation of the Higher-Order Fac-tors

Second, according to Rindskopf and Rose (1988) the bi-factor model has the weakest structure and consists of one bi-factor and multiple group factors. The bi-factor model is a latent structure where each item is loaded onto a bi-factor. This bi-factor reflects what is shared between the subjects and represents the individual differences in the target dimension that the researcher is most interested in. In addition, the bi-factor model specifies orthogonal two or more group factors (Dunn and McCray 2020). These group factors are common factors measured by items that potentially explain the variance in response to an item not reflected in the general factor. Prio to applying an EFA to determine the factor loadings, we define the structure of our bi-factor model. To build such a bi-factor model, we defined 12 group factors, which may not correlate with each other, and one bi-factor, which is orthogonal to the group factors, i.e., may not correlate with them either. For the EFA, we used the approach according to Jennrich and Bentler (2011), and for later validation in the context of a CFA, we will perform the mapping as revealed in the loading of the EFA (Appendix F.5).

Validating the Concept of Demands from Digital Work

Finally, we used a new data set (n_2 = 3,000) and covariance-based structural equation modeling to first decide on the structure of demands from digital work that fits best and then to embed it in a nomological net.

For the final validation of the measurement instrument, a large data set (n_2 = 3,000) was collected using the same external research panel as for the previous data set (validation sample). Respondents were paid 3,10 € for their participation. We included control variables to review the representability of our sample. These comprised gender, employment status, occupational title and sector, number of hours worked per week, and education. The participants' distribution was representative for the German workforce for the control variables age, gender, and sectors. Table 26 gives an overview of our participants' demographic properties of the validation sample and Appendix F.6 lists the psychometric properties of our final scale using the validation sample. Furthermore, we added two outcome-related constructs to assess nomological validity. One item is productivity and the other one job satisfaction. Productivity as self-evaluated work performance is measured with four items (Chen and Karahanna 2014). An example item is *"I have a reputation in this organization for doing my work very well".* Job satisfaction is the extent to which an employee likes his or her work. It is measured with six items (Agho et al. 1992). An example item is "*I am quite satisfied with my work*".

Gender	***N***	**%**	**Employment**	***N***	**%**
Male	1,623	54	Full-time (>20 h)	2886	96
Female	1,377	46	Half-time (<20 h)	114	4
Age (*M* = 43.19)	***N***	**%**	**Technology Use**	***N***	**%**
<25	108	4	Never	0	0
25-34	704	23	Seldom	0	0
35-44	815	27	Weekly	192	6
45-54	766	26	Daily	330	11
55-64	593	20	Several Times	2478	83
>65	14	<1			

Education	***N***	**%**
No Diploma	0	0
Primary School Education	49	2
Secondary School Education	360	12
Tertiary Education / High School Diploma	310	10
Completed Apprenticeship	985	33
College Degree (Bachelor)	491	16
College Degree (Master)	694	23
Dissertation (PhD)	111	4

Table 26: Demographic Properties of the Validation Sample (n_2 = 3,000)

We conducted Harman’s single factor test to derive whether CMB seems a problem in our data. All items were subject to principal components analysis (Podsakoff et al. 2003). Furthermore, we applied a correlational marker technique as a post hoc test (Lindell and Whitney 2001; Richardson et al. 2009). Both analyses conclude that CMB is considered as uncritical (details in Appendix F.7).

We again evaluated our models’ fit according to standard fit measures like RMSEA and SRMR for global measures, CFI, TLI, and NFI for incremental measures, and AGFI to assess the parsimony. We do not report χ^2 or χ^2/df as these are not considered meaningful for samples of our size. The results are displayed in Table 27.

Fit measures		**Threshold**	**Source of threshold**	**Second-order**	**Correlated group factors**	**Bi-factor**
Global measures	RMSEA	< 0.06	Lei and Wu (2007)	0.050	0.048	0.063
	SRMR	< 0.05	Gefen et al. (2000)	0.049	0.044	0.126
Incremental measures	NFI	> 0.90	Gefen et al. (2000)	0.926	0.932	0.889
	TLI	> 0.90	Gefen et al. (2000)	0.930	0.934	0.888
	CFI	> 0.90	Gefen et al. (2000)	0.934	0.940	0.897
Parsimony	AGFI	> 0.80	Gefen et al. (2000)	0.866	0.872	0.830

Table 27: Fit Measures from a CFA on the Validation Sample (n_2 = 3,000)

The data suggested that the bi-factor model is not a good fit. On the contrary, both the second-order and the correlated group factors model fit the data reasonably well. Thus, we suggest adopting the second-order model of demands from digital work. The primary reason is that it has a stronger structure with fewer parameters and is more parsimonious. Parsimony is generally considered a beneficial characteristic of theoretical models (Popper 2005, pp. 131, 272).

Next, we turned to embed the second-order model in a nomological net (Figure 22). Based on prior literature, we decided to investigate job-satisfaction and productivity as consequences from demands from digital Work (Tarafdar et al. 2010). Like Tarafdar et al. (2007) and Ragu-Nathan et al. (2008) we assume that they are affected not by first-order demands but by second-order demands. Unlike Tarafdar et al. (2007) and Ragu-Nathan et al. (2008) we do not consider a single second-order factor but four of them. Besides, sex, age, and frequency of technology use for the execution of work tasks are relevant control variables embedded in the model.

We hypothesize that awareness of potentially being supervised or information being provided to third parties leads to an unpleasant working environment. Therefore, we expect the second-order factor exposure to be negatively associated with both job-satisfaction (H1a) and productivity (H1b). Besides, the steady presence or absence of digital technologies might lead to frustration and less satisfying work results, for example, when a task could be easily completed with technology or not available at work. For this reason, we anticipate the second-order construct impediment to be negatively linked to job-satisfaction (H2a) and productivity (H2b). Furthermore, we expect a decreasing reliance on existing skills while, on the contrary, a constant need for refreshing one´s skills to be exhausting. Thus, we anticipate the second-order factor impediment being inversely related to job-satisfaction (H3a) and productivity (H3b). Finally, being held off executing one´s own tasks due to digital technologies is mentally draining and prolongs the completion of tasks. Thus, we expect interference to be negatively associated with job-satisfaction (H4a) and productivity (H4b).

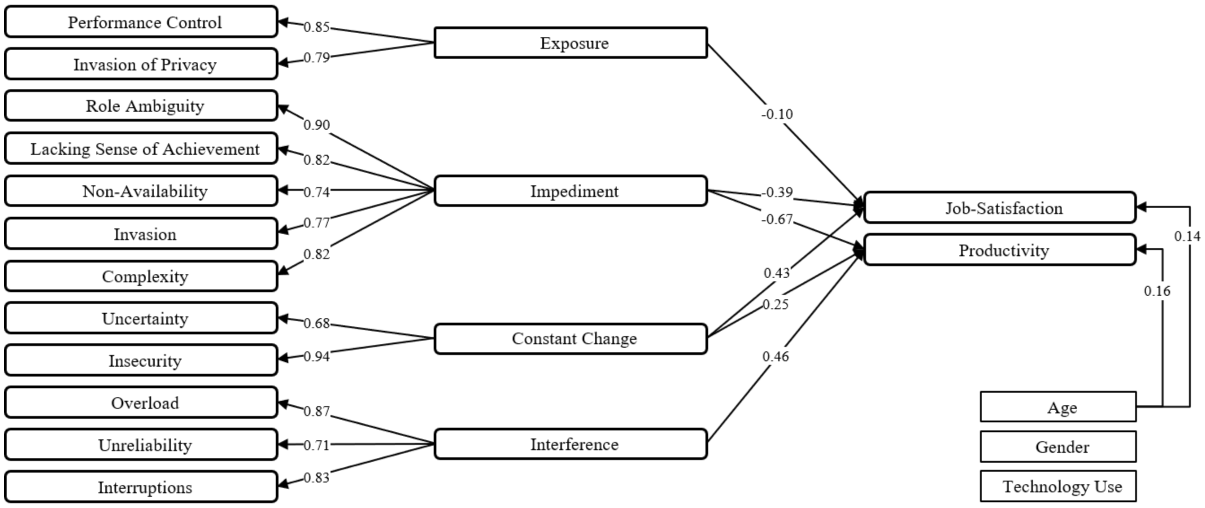


Figure 22: Nomological Net of Demands From Digital Work and its' Consequences

The model fits the data well. NFI, TLI, and CFI (NFI=0.92, TLI = 0.92, CFI=0.93) have good values just like RMSEA and SRMR (RMSEA = 0.05, SRMR= 0.05) for the incremental fit and AGFI for the parsimony of the model (AGFI = 0.89). The analysis results show that all first-order factors load on their assumed second-order factor with loadings ranging between 0.68 and 0.94. Out of the three control variables, we observed a significant effect of age on both, job-satisfaction ($\beta = 0.14$, $z = 7.39$, $p < .00$) as well as productivity ($\beta = 0.16$ $z = 8.46$, $p < .00$), but no effect of technology use or sex on either of the dependent variables, showing that with increasing age, employees are more satisfied with their job and experience themselves as being more productive. Regarding the independent variables, impediment ($\beta = -0.39$, $z = -4.77$, $p < .00$) and exposure ($\beta = -0.10$, $z = -2.31$, $p = .02$) negatively relate to job-satisfaction whereas constant change is positively associated with job-satisfaction ($\beta = 0.43$, $z = 6.91$, $p < .00$). The relationship with interference was not significant. Thus, H1a and H2a can be confirmed, while H3a and H4a have to be rejected. Impediment is also negatively associated with productivity ($\beta = -0.67$, $z = -7.56$, $p < .00$). Further, interference ($\beta = 0.46$, $z = 4.20$, $p < .00$) and constant change ($\beta = 0.25$, $z = 4.46$, $p < .00$) are both positively related to productivity. The relationship with exposure was not significant. Therefore, H2b can be confirmed, while H1b, H3b, and H4b have to be rejected. Overall, this analysis shows that the newly identified demands from digital work and their structure with four second-order demands integrated well with relevant and well-known consequences of stress at work.

Discussion

This chapter sets out to provide a contemporary perspective to the established research stream of psychological stress from work with digital technologies. The context of work changed substantially under the umbrella term of digital transformation (Vial 2019). We followed recent calls to update understanding of demands from digital work that cause stress (Fischer et al. 2019; Tarafdar et al. 2019) and address broader calls for contextualizing theories in IS research (Hong et al. 2014). We united nine different demands from digital work found in prior research in a single model. Based on qualitative interviews and focus groups, we identified three novel demands from digital work and added them to the model: non-availability, performance control, and lacking sense of achievement. In a series of quantitative survey-based studies, we discerned four higher-order demands from digital work (exposure, impediment, constant change, interference). We validated stressful demands from the use of digital technologies and media in the context of digital work.

Stress is a highly individual and situational process. Demands differ over time and between individuals. Yet, the ranking of average demands from digital work based on intensity reported by the 3,000 employees from the validation sample is informative (Table 53). In terms of aggregate values, employees perceive the strongest demands from performance control and invasion of privacy. This indicates that employees are highly concerned about how their data is handled within the company. With new possibilities of employee monitoring by digital technologies on the rise, this is not striking (Manokha 2020). Yet, the concept of technostress developed by Tarafdar et al. (2007) and the most used measurement instrument for assessing technostress creators developed by Ayyagari et al. (2011) does not cover these demands. Besides handling data, the third strongest perceived demand is regarding unreliable technologies. Perceived technological-induced stress due to technology that will not work, again, seems self-evident. However, this aspect is not integrated into the concept of technostress either. Overall, the ranking shows that the three newly identified demands from digital work do not lag behind the established ones. Thus, extending the set of demands to the contemporary work context reduces parsimony and adds important facets to understand today's psychological demands at work.

Considering specifically the nomological validity of the higher-order factors, at first sight, some of our results seem counterintuitive because two factors in the nomological net were positively associated with productivity and/or job-satisfaction. Constant change goes along with higher job satisfaction and higher productivity of employees. Further, interference is also positively associated with self-reported productivity. At second sight, two possible explanatory mechanisms may be in effect: challenge stressors and/or processes to reduce cognitive dissonance. It might even be an interplay of the two processes.

In the transactional stress model (Lazarus and Folkman 1984) the third kind of stress appraisal is “challenge”. It has much in common with the threat appraisal as it also activates coping resources, but it also has a motivational aspect. This form of appraisal focuses “on the potential for gain or growth inherent in an encounter and …[is] characterized by pleasurable emotions such as eagerness, excitement, and exhilaration” (Lazarus and Folkman 1984, p. 33). This aspect of technostress was also acknowledged by Tarafdar et al. (2019), who notion the term “techno-eustress” with the question to investigate “how and why individuals appraise IS as challenging or thrilling, experience consequent ‘good’ stress, and are faced with positive outcomes” (Tarafdar et al. 2019, p. 14). Benlian (2020) also found technology-driven challenge stressors along with technology-driven hindrance stressors. The factor constant change comprises uncertainty and insecurity. If an employee feels that (s)he lacks behind and the competence in handling digital technologies is not sufficient, it could motivate them to learn. If one invests time and effort to learn and is, in the best case, successful, it could lead to satisfaction and the final evaluation of being productive.

The second mechanism stems from social psychology: the phenomenon of cognitive dissonance (Festinger 1957, p. 179). If a person holds two beliefs that do not fit together, it creates tension as an unpleasant emotional state and triggers cognitive processes to reduce negative feelings. The factor interference comprises interruptions, overload, and unreliability. A person who is often interrupted and feels that the work can hardly be handled might not want to admit feeling stressed because being overwhelmed by the work could signal to be a low performer. It seems likely that the situation is reinterpreted as being in an outstanding position with many responsibilities. The long working hours are expressing commitment and necessary interruptions for alignment.

Advancing the Concept of Technostress to Digital Stress

Given the substantial transformation of work and the novel perspective of demands from digital work, it might be advisable to reconsider the concept of technostress itself.

As mentioned above, the term “technostress” was introduced 1982 when the Internet was still in its infancy. Since then, the definition got revised and expanded over time (Table 28). All of these definitions focus on the user's inability to deal with technology adequately, and some of them even seem to “throw the burden of technostress onto the users” (Sellberg and Susi 2014, p. 200). However, some dimensions of technostress do not concern the user’s capability to use technology adequately. For example, technology-induced stress can occur due to system malfunctions or a lack of appropriate technologies to accomplish a task. To take these dimensions of technology-induced stress into account, a broader definition of technostress is needed. Furthermore, even though technostress's concept and definition were revised and expanded over time, the terminological and theoretical framework is closely related to its period of origin. Since this period, technology, its use, and perception have changed drastically. While the Internet has become an universal source for information, new additional digital technologies and media like smartphones, social media, tablets, or digital TV have arisen and conquered work and private life (Chiappetta 2017). Therefore, because of its constricting definition as well as a changing perception and interaction with technologies, "the term of Technostress acquires a new meaning" (Chiappetta 2017, p. 359). However, we go beyond Chiappetta’s (2017) call for research and suggest using the term ‘digital stress’ instead of technostress.

Technostress	
Source	**Definition**
Brod 1984, p. 16	Technostress is a "modern disease of adaptation caused by an inability to cope with new computer technologies in a healthy manner."
Arnetz and Wiholm 1997, p. 36,	Technostress is a "state of mental and physiological arousal observed in certain employees who are heavily dependent on computers in their work."
Weil and Rosen 1997, p. 5	Technostress is "any negative impact on attitudes, thoughts, behaviors, or body physiology that is caused either directly or indirectly by technology."
Tarafdar et al. 2007, p. 304	"Technostress, therefore, is one of the fallouts of an individual's attempts and struggles to deal with constantly evolving [digital technologies] and the changing cognitive and social requirements related to their use."
Wang et al. 2008, p. 3004	"In Summary, we define technostress as a reflection of one's discomposure, fear, tenseness and anxiety when one is learning and using computer technology directly or indirectly that ultimately ends in psychological and emotional repulsion and prevents one from further learning or using computer technology."
Salanova et al. 2013, p. 423	Technostress is a "negative psychological state associated with the use or threat of digital technology use in the future."
Tarafdar et al. 2019, p. 7	Technostress is "stress that individuals experience due to their use of Information Systems."

Digital Stress	
Source	**Definition**
Hefner and Vorderer 2016, p. 237	Digital stress has been defined as the "stress resulting from a strong and perhaps almost permanent use of information and communication technology… that is triggered by permanent access to an inconceivable amount and diversity of (social) content."
Reinecke et al. 2017, p. 6	Digital stress is defined as "stress reactions elicited by environmental demands originating from digital technology use."
Fischer and Riedl 2020, p. 219	"Digital stress is a form of stress, which is caused by interaction with information and communication technologies and by their omnipresence in economy and society."

Table 28: Exemplary Definitions of Technostress and Digital Stress

Even though these terms seem to be interchangeable, we think they differ from each other. As mentioned above, technostress is often defined narrowly by focusing on adult users' role in a workplace context. Instead, digital stress across all proposed definitions has a general broader meaning (Table 28). Fischer and Riedl (2020) emphasize the use of digital stress beyond the workplace context by defining digital stress as "a form of stress caused by interaction with information and communication technologies and by their omnipresence in economy and society“. The term digital stress is broader because it terminologically includes digitalization at large as a source of stress rather than focusing only on its impact on work environments. In this, we consider digitalization to be a socio-technical phenomenon and processes of adopting and using digital technologies in broader individual, organizational, and societal contexts (Legner et al. 2017).

Further, the term digital stress is less technology-centric than the term technostress and thereby better represents the fact that it is not alone the technology that creates the stress but instead our individual and collective use of and perspectives on the technologies and media. In addition, several definitions of technostress (e.g., Tarafdar et al. (2007), Salanova et al. (2013)) focus on technology use. Yet, use is not required for stress to emerge when considering the threat of losing one’s job due to new digital technologies automating work (techno-insecurity (Ragu-Nathan et al. 2008; Tarafdar et al. 2007)) or non-availability of technologies.

The term digital stress contains all aspects of the technostress concept while also allowing the inclusion of further aspects of technological-induced stress, which have arisen in digitalization. Interactions with information and communication technologies, for example, comprise both the role of the user and the role of (unreliable or non-available) technology. In addition, Steele et al. (2020) attribute an essential role to digital stress to understand how digital media in general and social media affect adolescents and young adults. Against this background, Weinstein and Selman (2016) identify several digital stressors like pressure to comply or public shaming and humiliation by investigating the private use of digital media of adolescents. Furthermore, by merging the concept of technostress into the concept of digital stress, we see a chance in terminologically unitizing the multidisciplinary research field of technological-induced stress. Right now, “the use of numerous terminologies for similar or identical constructs complicates the literature” (Steele et al. 2020, p. 18). Focusing on a single term including research aspects of both private and work life over a life span from young to elderly would prevent obscuring results among studies and therefore make it easier to bring together the results of different disciplines and to understand the phenomenon of digital stress in its entirety (Steele et al. 2020). The comparatively new nomenclature as digital stress enables unifying different terminologies used in literature and integrating new phenomena and contemporary work practices relating to digital technologies that cause stress.

Considering prior definitions of technostress and digital stress, we define digital stress as the biological, emotional, and/or cognitive reaction of an individual to an imbalance between the availability of resources and coping measures and demands directly or indirectly imposed on the individual through the interaction with digital technologies. These demands result either directly from the use of digital technologies by the individual, indirectly by the digital technologies themselves, or from the use of digital technologies and media by third parties. For digital technologies and media, we adapt the definition of digital technologies from Bharadwaj et al. (2013, p. 471), who define them as "combinations of information, computing, communication, and connectivity technologies". While the given definition comprises both digital stress within a private and work context, our empirical analysis solely focused on the latter: digital work stress. Our definition of digital stress builds on the transactional model by Lazarus and Folkman (1984). Thus, digital stress includes an individual's subjective appraisal of an external event or stimulus based on one's own social and relational context as well as coping resources (Steele et al. 2020). In our context and following the wording from Lazarus and Folkman (1984), an external event is called a digital demand. Depending on the individual's perceived coping resources and relational context, the subjectively experienced digital stress level varies. If the individual concludes that the given resources are sufficient, no digital stress is experienced. Elsewise, digital stress is the individual's response. Finally, reactions to digital stress experience could include physiological, affective, or behavioral responses (Hefner and Vorderer 2016; Riedl 2012; Steele et al. 2020).

Implications for Theory and Research

Our research reevaluates the current concept of technostress and its creating factors in the context of contemporary digital work practices. We answered the question brought up by Fischer et al. (2019), whether the measurement instrument of technostress is still up to date and additional aspects can simply be added to the existing framework. We take the position that it is not sufficient to simply expand the scope of established technostress creators. It does not do justice to the complexity of the topic. The interaction with and use of technologies has considerably changed over the last ten to fifteen years, along with the societal and individual expectations. The interdependence of communication and information channels and the availability of new technologies gives rise to novel use cases and interaction forms through and with technologies. Against this background, our research makes the following contributions:

First, we present an holistic set of the most important demands from digital work. Nine of these twelve demands were considered in technostress literature before, for example, Tarafdar et al. (2007), Ragu-Nathan et al. (2008), Ayyagari et al. (2011), and Galluch et al. (2015). We combined them in a single unified model. Further, we added three additional demands from digital work that tax or potentially exceed worker's resources, creating stress: non-availability, performance control, and lacking sense of achievement. Research in IS and related disciplines has a current focus on stress appraisal (e.g., Benlian (2020), Califf et al. (2020)), stress coping (e.g., Tarafdar et al. (2020), Pirkkalainen et al. (2019)), stress outcomes (e.g., Chen et al. (2019), (La Torre et al. 2020)), and the design of stress-sensitive systems (e.g., Adam et al. (2017), Jimenez and Bregenzer (2018)). When stress from work with digital technologies and media is of concern, all these endeavors should consider our unified and updated conceptualization.

Second, empirical evidence and theoretical reasoning bring to light a higher-order structure with four second-order demand from digital work. Prior research has already considered higher-order models (e.g., Tarafdar et al. (2007), Ragu-Nathan et al. (2008), and research building on these articles). Yet, it suggested a single unitary second-order factor. With the context of contemporary work practices, our substantially broader conceptualization of demands from digital work and our large empirical samples, we see that the structure is multi-faceted. Hence, we newly introduce the second-order demands impediment, interference, constant change, and exposure. We believe that this structure eases the use of the otherwise not arranged set of demands from digital work. More importantly. We encourage fellow researchers to consider these higher-order demands in their quest for preventive and reactive measures to managing stress from work with digital technologies and media.

Third, we suggest evolving the concept of technostress to digital stress. We expect that this suggestion is controversial. One of the manifold potential objections could be that terming anything as "digital" is a fad that will fade. It might be considered a meaningless transient wording. Second and more concerning, some might fear a discontinuity in the well-established (IS) research stream on technostress. We partially share these concerns. Yet, because of its broader definition, a theory of digital stress as an extension of technostress can consider more aspects of modern private and occupational technology use by individuals over a life span from young to elderly. By doing so, such a theory of digital stress may contribute to terminologically unitizing the multidisciplinary research field of technology-induced stress. Future research should engage with the concept of digital stress, challenge, and evolve the definition provided here and develop the nomological net around it in various contexts.

Fourth, we developed and validated survey-based measurement scales for the newly identified constructs along the way of developing the first and second contributions. Further, we validate the scales' compatibility for established demands from digital work that have not yet been considered jointly. These scales may be used in future research to measure demands from digital work.

Implications for Practice

Our findings contribute to managerial practice in two ways. First, we raise awareness of digital stress and its several components, which go beyond the established concept of technostress. Especially in times where companies, politics, and the public, are trying to keep up with the increasing digitalization and all its expected benefits, it is important to emphasize potential negative effects because these effects can only be counteracted or prevented if they are known. Second, we go beyond raising awareness and offer a psychological risk assessment tool within the workplace context. With the help of our measurement instrument for digital stress exposure, companies can determine which one of the twelve demands from digital work is relevant in their working environment. Based on these finding, specific measurements for prevention or counteracting could be developed and implemented.

Evaluation and Limitations

According to Gregor (2006), our conceptualizing of demands and digital stress constitutes a type IV theory for explaining and predicting. We propose that digital stress is a biological, emotional, and/or cognitive reaction of an individual to an imbalance between the availability of resources and coping measures and demands directly or indirectly imposed on the individual through the interaction with digital technologies. Digital stress in the work domain arises primarily from twelve demands of digital work combined in a hierarchical structure of four second-order constructs: impediment, interference, constant change, and exposure. Each of these constructs is associated with job satisfaction and productivity. According to Weber (2012), we suggest evaluating our theoretical contribution, as shown in Table 29.

Criterion	Summary Evaluation
Parts	
Constructs	We precisely deduced all constructs from literature and qualitative interviews according to our mixed-methods approach. We provided definitions for all constructs: digital work, digital technologies and media (this section), twelve first-order demands from digital work (Table 22), four second-order demands from digital work (Table 25), job satisfaction and productivity (Figure 22), digital stress, and digital work stress (this subsection). The boundary condition for the demands and their consequences is digital work. The demands and their consequences apply to the individual worker level.
Associations	We show and empirically tested the associations of all constructs. The demands originate from digital work and affect job satisfaction and productivity. The first-order demands are consolidated to second-order demands as shown in 0Figure 22.
States	Demands from digital work, job satisfaction, and productivity each have a continuous state space. While typically there will be correlations (or non-linear associations) of the state, theoretically, any combination if individual states is possible.
Whole	
Importance	Excessive stress from digital technologies and media leads to negative humanistic (e.g., reduced satisfaction, well-being, health) and instrumental outcomes (e.g., reduced productivity, increased job turnover). Since not only the sheer number and functionalities of digital technologies have enormously increased in the last ten to fifteen years but also the interaction with these technologies has considerably changed due to availability, a changed individual and social view of technologies and expectations regarding digitalization, the concept of technostress needed a review.
Novelty	While technostress is already an extensively researched concept, we extend it to digital stress. Further, we unite, extant, and deduce three new demands from digital work and reveal their higher-order structure.
Parsimony	The quantitative evaluation shows that the reduction of parsimony compared to prior conceptualizations of technostress allows for a better explanation (and prediction) of consequences of work stress. Although our model on digital stress contains many different constructs, the second-order structure provides parsimony.
Level	Our contribution resides on the meso level.
Falsifiability	As we clearly defined the constructs and associations and provide measurement instruments for all constructs, our model can be subjected to further empirical tests. Thus, it can be falsified.

Table 29: Evaluation of our Contribution to Digital Stress Theory

Our research has some limitations. First, our sample in the qualitative study is not representative for all employees. Although we collected qualitative data of 61 individuals in expert interviews and focus groups, we did not select the individuals to be representative of the German workforce according to, for example, gender, age, or industry. Second, in our conclusions that we drew from the qualitative data, we did not consider whether a participant represented a larger industry or employee group in the working world than another participant but took their statements into account equally. However, by following a mixed-methods approach and combining the qualitative strand with a quantitative one, we were able to overcome these two issues by testing our qualitative results in a large-scale quantitative analysis. Third, we collected the quantitative data with the help of online surveys providing financial incentives. Typical weaknesses of this method, such as self-selection of the population, non-response, and questionable reliability of expressed opinions (Nayak and Narayan 2019), have to be considered in our research. Fourth, our three newly created dimensions non-availability, lacking sense of achievement, and performance control were tested with multiple large data sets, but only with employees in Germany. Future work may validate our results in other economic and cultural backgrounds. Fifth, it was tough to interpret the higher-order factor impediment. Therefore, future work needs to test these higher-order factor analyses with a different data set to check for stability and consistency and different potential compositions of higher-order factors. Sixth and last, we embedded our factors in a nomological net with job satisfaction and productivity. Future research should consider them with regard to potential antecedents (e.g., use or characteristics of digital technologies), further consequences (e.g., appraisal, coping behavior), or moderators (e.g., resources such as individual characteristics).

Conclusion

Digitalization is one of the most significant socio-technical challenges of modern humankind, transforming the way to work tremendously. This changes both the demands on employees and thus our theoretical understanding of the world. Our research contributes to understanding these new demands on employees in the age of digital work and thus laid the foundation for further research.

7. General Discussion and Conclusion

7.1. Summary of Results and Meta-Inferences

This dissertation consists of several research activities with the objective of designing the digital workplace to promote healthy interaction with DTM. For this purpose, different research methods from the fields of behavioral science and design science are used. The individual research activities provide knowledge chunks (Vom Brocke et al. 2020) derived from the analysis of the humanistic and organizational outcomes resulting from the reciprocal interaction within the socio-technical system and the experience from designing socio-technical systems. These knowledge chunks complement the Ω-knowledge base (i.e., collectively gathered descriptive and explanatory knowledge) and λ-knowledge base (i.e., collectively gathered prescriptive knowledge).

In general, four types of goals can be distinguished, which a knowledge chunk could pursue (Gregor 2006). Three goals lead to an extension of the Ω-knowledge base and one goal leads to an extension of the λ-knowledge base (Drechsler and Hevner 2018). Knowledge with the goal *analysis* describes the phenomena of interest and analysis relationships, whereas knowledge with the goal *explanation* goes one step further and provides rationales for these relationships. Knowledge with the goal of *prediction* uses information from the previously mentioned goals to predict what will happen when certain conditions occur. Knowledge with the *prescription* goal also uses previously collected information from the Ω-knowledge base (Drechsler and Hevner 2018) and describes how an action can be completed. Thus, knowledge with the goal *prescription* leads to an extension of the λ-knowledge base. Within the λ-knowledge base, the knowledge contained here can be divided into the category *design entities* (e.g., knowledge from artifact instantiations, knowledge about the design process of artifacts, knowledge about the evaluation of concrete artifacts) and *design theory* (e.g., design requirements, design principles, design techniques) (Hevner et al. 2019).

In the context of specific research activity, knowledge is extracted from the Ω- or λ-knowledge base, or both, to conduct behavioral science research (which primarily expands the Ω-knowledge base) and design science research (which primarily expands λ-knowledge) (Gregor and Hevner 2013). A research activity consists of one or more modes and takes on one or more roles. Whereas a mode describes how a research activity interacts with a knowledge base (e.g., draw on the different knowledge types either to utilize them in a design science or behavioral science research project to produce prescriptive knowledge or descriptive knowledge), the roles presented in the subsection on Research Methods in Information Systems address which goal a research activity pursues. For example, in the context of a design science research activity, knowledge can be extracted from the Ω-knowledge base and λ-knowledge base (accordingly, two different modes are applied here) and inform the design and development of a technical component (this corresponds to role 1). Simultaneously, the findings are then incorporated into the λ-knowledge base (a different mode).

The mode is differentiated by which type of knowledge is consumed (Vom Brocke et al. 2020). Mode one draws knowledge from the Ω-knowledge base, while mode three and mode five draw from the λ-knowledge base. If the used knowledge is from a design theory, mode three is applied, and if the knowledge is from design entities, mode five is applied. However, a research activity's contribution is reflected in the production of knowledge and the associated expansion of the knowledge base. Again, three types of contributions to the knowledge base can be distinguished (Vom Brocke et al. 2020). Mode two refers to expanding the Ω-knowledge base and aims to analyze, explain, or predict what will result from a socio-technical system's reciprocal interaction. Mode four summarizes the accumulated knowledge from one or more research activities into design theories or complements existing design theories and informs the design of future socio-technical systems. Finally, mode six refers to the documentation of the designed socio-technical system and the demonstration of its utility. Mode four and also mode six thus contribute to the expansion of the λ-knowledge base.

Several research activities can also be intertwined, resulting in a complex interplay of modes and roles. If we look at Chapter 5, for example, it consists of three major research activities. In the first research activity in Section 5.1, a data collection framework, i.e., a technical component, was developed (role one) based on existing knowledge about the design of data collection systems (mode five), and the resulting knowledge was added to the λ-knowledge base (mode six). In subsection 5.2, the knowledge available in the Ω-knowledge base on the topic of stress (mode one) is combined with the knowledge available in the λ-knowledge base on the collection, storage, and processing of data (mode five), and a prototype for life-integrated stress assessment is developed (role one). Again, the resulting knowledge is added to the λ-knowledge base (mode six). In subsection 5.3, knowledge from many different design entities (mode five) is extracted from the λ-knowledge base (original knowledge arising from third-party research, knowledge arising from the research activities presented in this dissertation is now also included), which, over the course of the research activity, leads to a contribution for a mid-range design theory (role four), which is fed back into the λ-knowledge base (mode four).

This dissertation contributes to expanding the knowledge base according to modes two, four, and six. The interaction and expansion of the knowledge base discussed above are illustrated in Figure 23.

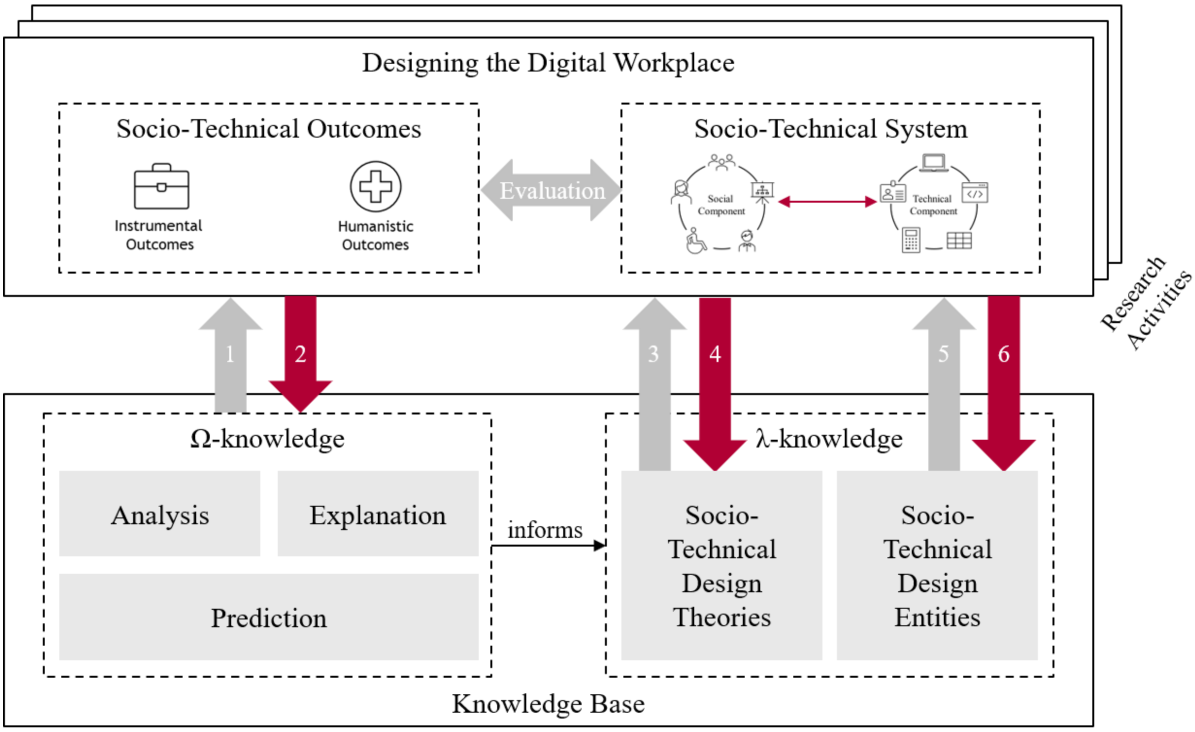


Figure 23: Interaction of Research Activities and Knowledge Bases

Theoretical Contribution

The research activities presented in this dissertation interact with the two knowledge bases in different modes and contribute to the expansion of the Ω-knowledge base and λ-knowledge base.

Extending the Ω-knowledge Base

Concerning mode two, the extension of the Ω-knowledge base, the contributions can be distinguished based on the focus regarding the socio-technical system. For example, the contributions from Section 3.1 consider properties' technical components and how they affect humanistic and organizational outcomes. Therefore, research in Section 3.1 contributes to the identification and definition of further characteristics of DTMs that affect technostress at an individual's workplace, including measurement scales for the newly added characteristics. Placing these newly identified characteristics side by side with the ones from extant literature (esp. from Ayyagari et al. 2011), our research presents the most holistic set of DTM characteristics related to technostress. Further, to the best of our knowledge, we are the first to combine the characteristics of Ayyagari et al. (2011) with the technostress creators of Ragu-Nathan et al. (2008) and can thereby show their relationships. Furthermore, we provide evidence for the relationship of the characteristics associated with different technostress creators instead of technostress in general.

The results from Section 3.2 and 4.2, on the other hand, consider how different aspects of the social component affect humanistic and organizational outcomes. For example, Section 3.2 and Section 4.2 both address aspects related to the organizational boundaries. Thereby, the results from Section 3.2 strengthen the findings of Self-determination Theory regarding the relationship between autonomy and well-being. More importantly, we demonstrate the underlying theory's applicability in the context of the design of DTM. Besides, we have shown that the effect of autonomy might not originate from its actualization, but that its offering might already be sufficient. We add to Affordance Theory as we empirically observed that the mere provision of affordance could affect the users' subjective well-being while self-tracking goals.

The results from Section 4.2 focus on the direct and indirect effect of demands resulting from DTM use on productivity. First, besides the negative indirect effect between job demands and productivity (through mediation via exhaustion), there is a positive direct effect. This positive effect means productivity increases as job demand increases, which seems contradictory. Reasons for this may be found in the curvilinear relationship between general stress or work pressure and performance (Hofmans et al. 2015; Leung et al. 2011). In other words, people who feel little demand can not utilize their full potential, resulting in low productivity. With increasing demands, productivity increases until a specific turning point is reached: If employees exceed this level and the perceived demands are too much, productivity drops (Janssen 2001). Another reason for this is a potential suppressor effect, which occurs when the direct and indirect effects on a dependent variable have opposite signs. Therefore, an inconsistent mediation is present (Tzelgov and Henik 1991). In the literature, it is considered realistic that two opposing direct and indirect effects with a similar magnitude almost neutralize each other, and therefore, the total effect is not significant (MacKinnon et al. 2000). However, we argue that, despite the positive relationship between job demands and productivity, technostress may lower productivity in a long-term view or have no positive impact on productivity. On the other hand, however, technostress increases the strain, leading to long-term health effects and negatively impacting organizational objectives from a long-term perspective. Therefore, technostress should be reduced for organizational and humanistic reasons.

In contrast, other results from Section 4.2 focuses on aspects related to personal preferences in dealing with technostress and its impact on humanistic and instrumental outcomes. Considering the role of coping to overcome technostress, results in Section 4.2 initially confirm prior research regarding the direct effects: A broad application of active-functional strategies is negatively related to exhaustion. In contrast, a broad application of dysfunctional coping may increase it. In doing so, dysfunctional coping exhibits a stronger direct impact on exhaustion. A possible explanation for this could be the nature of active-functional coping: Strategies from the active-functional category (such as actively seeking to change the stressful situation) require individuals' energy and cause cognitive effort in implementation, which, in turn, may reduce the buffering effect on exhaustion. In contrast, both active-functional and dysfunctional coping reduces the relationship between job demands and exhaustion. Furthermore, we observed considerably higher values for dysfunctional coping regarding the buffering effect on the relationship between job demands and exhaustion. This implies that even though dysfunctional strategies go along with higher exhaustion, their moderating effect on the relationship between job demands and strain is stronger compared to active-functional strategies. This is particularly interesting because dysfunctional coping is said to be detrimental.

Finally, results from Section 6 focus on understanding the perceived misfit in modern socio-technical systems. First, we present a holistic set of the twelve most important demands from digital work. Nine of these twelve demands were considered in technostress literature before, for example, Tarafdar et al. (2007), Ragu-Nathan et al. (2008), Ayyagari et al. (2011), and Galluch et al. (2015). We combined them in a single unified model. Further, we added three additional demands from digital work that tax or potentially exceed worker’s resources, creating stress: non-availability, performance control, and lacking sense of achievement. Further empirical evidence and theoretical reasoning bring to light a higher-order structure with four second-order demand from digital work. With the context of contemporary work practices, our substantially broader conceptualization of demands from digital work and our large empirical samples, we see that the structure is multi-faceted. Hence, we newly introduce the second-order demands impediment, interference, constant change, and exposure. We believe that this structure eases the use of the otherwise not arranged set of demands from digital work. Lastly, we developed and validated survey-based measurement scales for the newly identified constructs along the way of developing the first and second contributions. Further, we validate the scales' compatibility for established demands from digital work that have not yet been considered jointly.

Extending the Ω-knowledge Base and Informing the λ-knowledge Base

Results from Section 4.1 entail, due to the underlying longitudinal design, the possibility to extend Ω-knowledge base by knowledge chunks with the goal of prediction and thus offer the possibility to infer λ-knowledge. Research in Section 4.1 delivers descriptive knowledge regarding the socio-economic implications of telework enforced by the lockdown due to the COVID-19 pandemic and allows it to derive prescriptive knowledge. Therefore, the influence of different contextual factors on changes in the demands from digital work was examined and thus provides insights into which employees are affected by lockdown-induced telework. Concerning technostress, employees with less self-efficacy and telework experience are more affected, concerning private demands and resources, factors such as caring responsibility matter. However, this does not increase overall technostress or one of its individual technostress creators. Surprisingly, managers were less affected by enforced telework than other employees. However, this only regards technostress, and we do not have further insights into other responsibilities that come with a management position (e.g., role model for employees, change management). Additionally, Srivastava et al. (2015) pointed out how managers react differently to technostress by showing that technostress can also result in positive outcomes. Based on the results of the empirical analyses and the discussions during the events, measures can be derived. For example, employees should be empowered to conduct telework during part of their working time. This creates the necessary conditions concerning spatial equipment and the availability of digital devices and services. In addition, employees gain experience with telework, which can lead to greater self-efficacy and enhance employees' trust in their own ability. In summary, this may reduce the adverse effects of teleworking on technostress and show preventive indications for measures to steer these effects if the situation persists or comparable disruptive situations should re-occur.

Informing Existing and Developing new Design Theories for the λ-knowledge Base

In order to extend the λ-knowledge base, this dissertation compiles knowledge chunks related to mode four that either represents a first step on the path of a design theory by deriving good-practices from prototypes or that contribute to a mid-range design theory. For this, the results of Section 3.2 and Section 5.2. yield lessons learned from the technical components they contain that inform the future design of other technical components, while Section 5.3 contributes to a mid-range design theory.

Concerning the developed technical component in Section 3.2, users should be able to enter goals that do not necessarily have at least one goal-pursuing activity a week. The app should allow goals with differing activity-rhythms as well. Next, users should be able to pass on goal-pursuing activities and not be restricted to either marking them as done or failed. This way, the app could implement pauses in the goal-directed behavior due to illness or vacation, track the users' activities more accurately, and afford the users with additional autonomy. The proposed refinements should improve the app's usability, the amount of time for which users stay with the app, and the quality of the captured data. Addressing the lessons learned during agile prototyping the technical component aiming at a life-integrated stress assessment in Section 5.2, we gained various important insights into critical success factors of life-integrated stress assessment. In their combination, these learnings help with details on the design of life-integrated stress assessment and might help researchers and practitioners likewise build better DTMs. Most importantly, the accessibility of stress assessment is vital for its use and acceptance. Obtrusiveness, or the necessity of attention or interaction with the user, puts up high barriers for broad application. Our research shows that life-integrated stress assessment is feasible and a valuable approach to stress assessment. Nevertheless, it also shows that excessive resource consumption, in terms of data storage or upload, battery consumption, or processing power, might already be partially obtrusive. It brings the system's existence to the user's attention. Another important facet is to consider the protection of the user's privacy. For some people, the stress level itself is highly sensitive information. This holds especially true when the information is shared with others(e.g., with the employee's supervisor) in organizational stress management applications. Privacy is even more important with the full set of sensor data that allows for movement, usage, and behavior profiles. Consequently, applications should establish appropriate privacy protection mechanisms that prevent external access to sensitive information on a need-to-know basis (Sutanto et al. 2013). One potential measure could be to fully renounce an internet-based data upload and perform computations fully on the user's device. As third learning, user feedback suggests they are significantly more tolerant toward limited privacy and resource-saving if the DTM provides a clear benefit to the user.

Section 5.3, on the other hand, builds on this and other knowledge and presents a design theory on the topic of mobile stress assessment. By analyzing the literature, we consolidated extant design knowledge formerly dispersed across various studies and derived design requirements, an abstract blueprint, design principles, and design features. Archetypes arising from subsequent cluster analysis give further impressions on how the design features are implemented in current practice. Building upon this design knowledge, we performed our prototyping activities, resulting in an understanding of trade-offs between design requirements and the design features. Overall, the design theory presented in Section 5.3 strongly builds on and combines extant design knowledge on MSA and is tested and expanded in our own prototyping activities (Vom Brocke et al. 2020). It contributes to the literature on the topic of MSA by providing researchers and practitioners with extensive design knowledge on how to develop effective MSA systems (as a contribution to the design theory knowledge base in the Vom Brocke et al. (2020) framework). Complementary, it contributes to DSR literature by providing an example of a theoretically grounded and empirically enhanced design theory that can inspire further researchers to strive for consolidated design knowledge in order to facilitate the development of effective IS.

Deriving Knowledge from Design Entities for the λ-knowledge Base

Additionally, various technical components were developed in the dissertation's research activities, which, together with their documentation of the results and the evaluation of their utility, also contribute to the λ-knowledge base according to mode 6.

In this way, research in Section 3.2 resulted in a measurement instrument by developing a mobile application that represents an easy way to capture the entirety of our model's constructs. Its design may facilitate similar research endeavors in the future. Once the app had been developed and distributed, it reliably and continuously captured empirical data and delivered it to our research team. The maintenance effort was limited to minor updates, and the data analysis could be automated. Although only four of the five hypotheses were supported empirically, our results support the positive effects of the provision of enhanced autonomy affordance on its actualization, goal performance, and subjective well-being. More importantly, we demonstrate the underlying theory's applicability in the context of the design of DTM for self-tracking, goal-directed behavior.

During the research in Chapter 5, various technical components were developed to determine a smartphone user's current affective state. The developed sensor-based data collection framework in Section 5.1 forms the basis for most developed technical components. It supports collecting and combining heterogeneous data in the area of individual health. Depending on the use case, the analysis represents a complex challenge. The proposed framework manages to handle varying datasets by implementing every issue as a single sensor, enabling various ways to save, combine, and analyze them. During the development of the technical component in Section 5.2, we followed the design science research methodology of Peffers et al. (2007) and elaborated the DTM in several steps. Based on problem relevance, theoretical background, and design requirements, we developed an exemplary implementation for the Android platform. This prototype helped demonstrate the general operationality of life-integrated mobile sensing and its applicability for assessing perceived stress. A binary classifier demonstrates its value for determining stressed and non-stressed mental states. The universal stress assessment regression model elaborated in this work links data from smartphone sensors to their application for stress valuation and confirms life-integrated and continuous stress assessment feasibility. This model is based on data gathered within a public field study, in which 40 users provided data by using the prototype. Therefore, the presented method enables developing systems that apply a life-integrated and continuous assessment of perceived stress as input for adaptation mechanisms that provide targeted technological or manual stress management interventions. Furthermore, the method can be used as an indicator for the user's current affective state to provide relevant information to user-adaptive systems, enabling a more intuitive interaction (Morana et al. 2017).

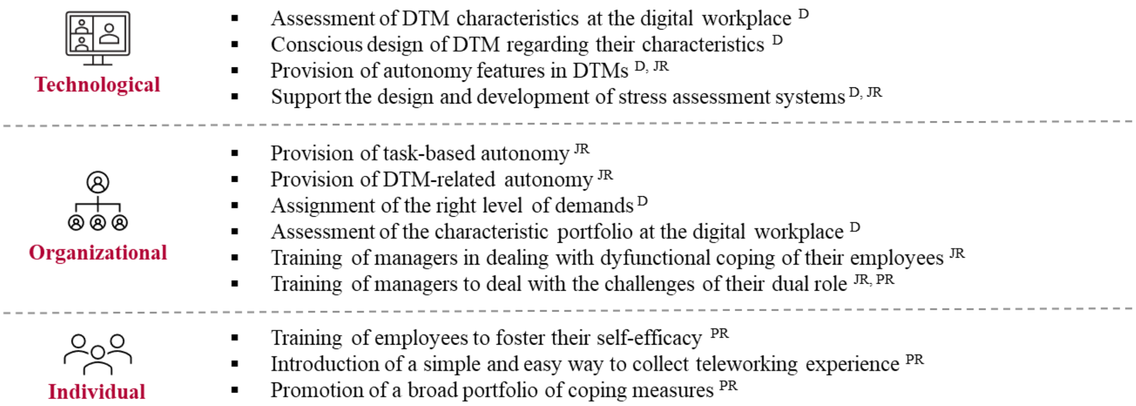
Besides other technical components building on the in Section 5.1 developed framework where implemented in Chapter 5 in order to derive new design knowledge on mobile stress assessment. Building upon the developed design knowledge from Section 5.3, we produced new design knowledge on design entities from developing five MSA prototypes for different intended applications. In this process, the collected design knowledge proved to be suitable and useful for MSA designed to be generalizable to various intended applications (Venable et al. 2016). The prototypes' evaluation in laboratory and field studies provides summative real-world evidence of the in Section 5.3 presented design theory's applicability and utility for developing effective and suitable MSA instantiations (Venable et al. 2016).

In documenting the technical components and evaluating their utility, numerous knowledge chunks related to these design entities have emerged. These and other knowledge chunks have contributed to the development of the design theory in mode 4.

Overall, this dissertation and the contained knowledge chunks resulting from a wide range of research activities contribute to expanding the knowledge base regarding the design of the digital workplace to promote healthy interaction with DTM.

Practical Implication

Research in the dissertation at hand also results in practical implications that will allow the digital workplace as a socio-technical system to be designed so that healthy use of DTM is possible. The findings relate to both the technical and social components, which again distinguish the social component in terms of the implications for the organization as well as the individual. The following measures to promote the healthy use of DTM are therefore presented for the three levers of technology, organization, and the individual, aiming to reduce the incidence of digital work demands or resources (job and personal) in dealing with these demands. Figure 24 summarizes all developed measures, which are further discussed in this subsection.



Notes: A superscript D implies that this measure aims at reducing demands, while a superscript JR and PR implies that this measures at promoting job and personal resources dealing with demands

Figure 24: Summary of the Developed and Analyzed Measures for the Three Levers

Technological Levers

The technological lever refers to the use of well-designed DTMs. As far as this lever is concerned, the measures developed in this dissertation can be divided into two categories: concrete measures for the design of a technical component used in the context of a socio-technical system and measures for a technical component intended to promote reciprocal interaction between a social component and another technical component. First, based on the features developed in Section 3.1 for the characteristics of DTMs, DTMs can be assessed on their possible susceptibility to technostress, such as by identifying technologies that exceed positive characteristics.

Furthermore, the characteristics help to consciously design DTMs in such a way as to facilitate reciprocal interaction with the social component.

In addition to these abstract characteristics, the recommendations in Section 3.2 may contribute to users' and employees' success and well-being while working toward their objectives by implementing autonomy features. In particular, as DTM is predetermined in organizational settings, employees could act significantly less autonomously. This highlights the need for autonomy features and emphasizes their potential to increase the well-being of employees. Conscious design of DTMs about their characteristics can lead to a lower intensity of digital work demands, whereby autonomy features also reduce the intensity (if they are part of the DTM responsible for the demands of digital work) or as a job resource (if they are integrated into a DTM that is supposed to support the handling of other DTMs).

Second, Chapter 5 supports software developers in designing and developing mobile stress assessment systems and provides them with abstract architecture and design guidelines, complemented by supporting information on possible trade-offs throughout the development process. This will make it easier to design and develop mobile stress assessment systems. Such systems form the basis of an IT-based stress management system, which can be seen as digital assistance in dealing with traditional demands in general and the demands of digital work specifically. These digital assistants are, therefore, a job resource. Simultaneously, mobile stress assessment systems provide the basis for a stress-sensitive adaptive enterprise system that can be adapted to employees' needs and therefore control the intensity of traditional demands and demands of digital work.

Organizational Levers

Organizational lever refers to organizational structures, processes, and guidelines. Measures for the design of work, the workplace equipment, and the definition of different roles can be derived concerning this lever. It should be noted that the transition from organizational to individual measures is seamless, as the organizational measures partly affect individuals' behavior. Regarding the design of the work, Section 3.2 supports the findings of various areas of IS research and psychology regarding the positive effects on performance and subjective well-being of the provision of enhanced autonomy. Therefore, employees should be granted a certain degree of autonomy as a job resource to pursue their tasks.

Additionally, the implications of Section 4.2 show that employers should ensure their employees are exposed to the right level of demands for a high level of productivity. Both minimal and excessive levels of demands should be avoided. Otherwise, the employee would be under-challenged or overcharged, which could result in lower job performance.

For workplace equipment, Section 3.1 recommends organizations focus on using high-value DTMs for usability characteristics, including usefulness, ease of use and reliability, and DTMs that enable mobility and pull configurations. Furthermore, it should also be taken into account that the workplace equipment is usually made up of several DTMs. Therefore the characteristic portfolio of the digital workplace as a holistic system, which is ultimately responsible for the demands of digital work, should be considered. In addition, individuals could impact the intensity of digital work demands by configuring their digital workplaces. Employers should also give their employees the flexibility to configure their DTMs as a job resource in the most beneficial way to each individual. A holistic view of the workplace characteristics and the level of work-related requirements can reduce the intensity of emerging demands. Simultaneously, both the autonomy provided in the execution of the task and the autonomy concerning DTMs help deal with the demands and thus act as a resource. However, in this context, reference should be made to Gimpel (2019), who has shown in a study that DTM Autonomy can be useful as a resource and act as an additional demand.

Regarding the effect of dysfunctional coping described in Section 4.2, it is important to be aware of the long-term health issues of dysfunctional coping. This can be where employees often use dysfunctional strategies (predominantly or in combination with active-functional strategies), and so employers should ensure they provide expertise on these long-term issues by establishing specific health initiatives. Employers should be aware of this double-edged sword and take preventive measures to identify persons at risk of becoming addicted. Also, managers should have dedicated training programs to provide them with the necessary know-how to identify and support potentially addicted employees.

Furthermore, managers are also particularly affected by the effects of DTM, as shown in the results of Section 4.1. Employees in the management position also report a higher intensity of demand from digital work, both before and during the lockdown, than employees without a management position. At the same time, the differentiation decreases during the lockdown so that the intensity decreases for managers. However, this only concerns the demands of digital work. We do not have any further insights into the other responsibilities that come with a management position (e.g., a role model for employees, change management). Also, Srivastava et al. (2015) have already pointed out that managers react differently to technostress by showing that technostress can produce positive results. Organizations should, therefore, always be aware that their managers are increasingly in demand due to their dual role as both creators of the working environment and those affected by the demands of digital work. Here, among other factors, there is a seamless transition between organizational and individual measures since, although organizational measures may seek to promote a certain behavior, the actual behavioral change ultimately lies with the individual.

Individual Levers

The individual lever refers to measures that address the individual employee's behavior. With this lever, the measures refer to a building up of personal resources for dealing with DTM. The results from Section 4.1 show that employees with less self-efficacy and telework experience are more affected by the lockdown than other employees concerning demands from digital work. This is even though self-efficacy is not competence in the narrower sense, but rather trust in one's abilities. Accordingly, organizations should promote the development of self-efficacy in remote working and telework experience, which have gained importance due to the forced changes in the wake of the COVID-19 pandemic. In addition to possible training to build skills and improve self-efficacy (Schunk 1989), easy access to teleworking in the aftermath of the COVID-19 pandemic could increase individual employees' experience. Thus, the benefits of the teleworking option can be retained permanently and possible risks can be mitigated.

Also, according to the recommendations of Section 4.2, employees who use a few different ways of coping should be encouraged to develop a more expansive repertoire of different coping strategies to address different kinds of stressful situations effectively. Simultaneously, employees who primarily use one type of strategy (active-functional or dysfunctional) are recommended to adopt the other category and be supported by their employer in expanding their coping behavior. All measures anchored on this lever relate essentially to personal resources. Although it would also be conceivable to link these measures to job resources, as, for example, training and similar measures are made available for the employees, the measures focus on a behavior change. They should, therefore, be assigned to the individual lever. This once again shows the seamless boundaries between measures at the organizational lever and the individual lever.

Valuation

Overall, the dissertation at hand addresses both humanistic and instrumental objectives while at the same time focusing on the reciprocal interaction between the social and technical components, neither of which is privileged. The dissertation broadens existing Ω- and λ-knowledge by applying pluralistic methodological approaches underpinning behavioral science and design science paradigms. Therefore, the dissertation takes in different perspectives on the reciprocal interaction between the social and technical components of the socio-technical system. In this way, it also contributes to the design of a healthy digital workplace in the face of digitalization, reflecting humanistic and instrumental objectives as the core of the IS discipline (Sarker et al. 2019).

According to Leidner (2020), the contribution of the dissertation at hand can be assessed based on different aspects, namely the contribution to the theory, the underlying research methodology, the framing in the sense of anchoring the existing literature, and the relevance of the phenomenon under study. First, as far as theory is concerned, the dissertation fills gaps in mature theories, expands mature theories, transfers existing theories from other disciplines to IS, and contributes to the development of new theories. Thus, the dissertation at hand covers a wide range of theoretical aspects and offers new perspectives on designing a healthy digital workplace. In many cases, the research presented here relies on multiple methodological procedures, such as longitudinal survey design, field experiment design, mixed-method design, or qualitative methods involving experts and employees. About the third aspect, framing, the presented research, in many cases, refers to the interdisciplinary field of computer science, IS, and psychology. Consequently, strands of literature from different disciplines are intertwined. At the same time, the needs for the respective research are highlighted and more than the isolated gaps in research are addressed. Even though Brod‘s (1982) technostress phenomenon was raised almost 40 years ago, the subject has gained enormous importance in the course of digitalization in recent years. It has been discussed even more prominently in the context of increased teleworking during the COVID-19 pandemic. Scientific literature, therefore, shows an increase in publications in the field of technostress (Bondanini et al. 2020). However, the importance of the phenomenon is also evident in everyday practice when, for example, publicly funded research projects (e.g., PräDiTec[7], ForDigitHealth[8]) deal exclusively with the effects of the use

[7] https://gesund-digital-arbeiten.de/
[8] https://gesund-digital-leben.de/

of DTM or more than every third employee reports heavy burdens due to at least one demand from digital work (Gimpel 2019). Thus, this dissertation's research explores an emerging phenomenon, even though technostress was first introduced in 1982.

7.2. Limitations and Outlook for Future Research

Limitations

Like other research, the dissertation at hand has limitations. However, these limitations also show the need for further research to fully grasp the complexity of the reciprocal interaction between the social and the technical component in the context of digital work. A description of the limitations of the research conducted in the dissertation and opportunities for future research beyond this dissertation are provided below.

Understanding the Technical Component

First, regarding the aim of Chapter 3 to better understand the technical component's role and its influence on employee health and productivity, the results do not cover all aspects and perspectives of a technical component that may be relevant to achieve this aim. Beyond that, the research process also offers the potential for improvement.

In Section 3.1, we build the technology profiles on the individuals' perception of characteristics and not by asking technology experts. However, stress is a construct that builds on the perception of a situation and the individual's own ability to cope with a particular situation. Therefore, from the individual's point of view, the perceived characteristics of DTMs in the workplace are key. To validate this, future research could investigate how experts' assessment differs from that of employees and how this affects the explicability of technostress. Second, each respondent to the survey assessed only the characteristics of one digital technology and not the characteristics of the digital technologies at the respondent's entire workplace. However, since our sample is of a high number, we were able to assign characteristics between subjects. Nevertheless, it could be more precise to have affected employees directly assess the perceived characteristics of DTM. It should be kept in mind that a clear distinction between an assessed characteristic as unevaluated demand in terms of external stimulus and an assessed characteristic as stressful-appraised demand is difficult to argue for and that comparability of assessments across individual employees is hardly tenable.

The research presented in Section 3.2 calls for further research on the interconnection of flexibility, goal performance, and well-being in DTM self-tracking. The data collected was not enough to verify our assumptions in one model, as the sample size was relatively small. As a next step, the study should be resumed after the refinements have been made to the developed DTM identified in the research. As a result, more data could be collected and the hypotheses could be verified with more sophisticated approaches. Second, both the survey and log data collected by myGoalJournal originate from user self-reports. Users have decided whether and what activities they have logged in and how. Furthermore, according to interviews with several users, their interpretation of non-logging and activity differed. For some users, not logging an activity has the equivalent meaning of logging an activity has failed. For other users, not logging an activity meant they forgot to log, and if they logged the previous days or weeks, the share of done and failed activities would have been similar to those of the previous days. Third, we analyze all observable user-level variables based on their aggregation. Some variables, like nature, difficulty, and motivation of objectives, can also be examined at the goal level. Variables like the logging result (done or failed) of an activity could even be analyzed at the activity level. Further research could focus on the same or interlevel relations of these variables. For example, the nature and motivation of a goal and the user's personality could be examined for cross-relationships. Finally, in the context of work, the organization usually determines both the objectives and the DTMs used to track the goals' progress. Unlike in a private individual, self-tracking context where users freely pick the DTM and their own goals, employees' behavior can be significantly less self-regulating. It stresses the need for autonomy-supportive functions and their potential to improve instrumental goals and employee well-being (Bakker and Schaufeli 2008).

Understanding the Social Component

Second, regarding the aim of Chapter 4 to better the social component's role in terms of contextual and individual factors of social circumstances and their influence on employee health and productivity, the results only partially cover the complicated relationship between the work, private and personal domains, which would have been necessary for a deeper understanding of the social component in order to achieve this. Beyond that, the research process also offers potential for improvement.

Research in Section 4.1 is limited in multiple ways. First, we develop our hypothesis based on six newspaper articles and eight interviews. Although we have been selecting interviewees and experts from different jobs and personal backgrounds, future research should aim for a larger sample and in the field of management in particular. Secondly, during the quantitative stage, we explicitly focused our sample on participants who had no major changes (i.e., changed employers, changed jobs, no reduced working hours and unemployment) compared to the pre-lockdown time period. Future research projects should also explicitly examine workers and their work and privacy, which were heavily impacted by COVID-19, to take special precautions regarding future scenarios. However, this decision has enabled us to examine how telework affects technostress. Furthermore, this section's research was empirically driven due to the topic's timeliness and dynamics, and the focus was more on the quantitative strand. Further research should embed the results from the qualitative and quantitative strands more firmly in the scientific literature and expand current knowledge on the effect of work, private, and personal context factors on technostress. This is particularly important since many studies on technostress in the literature are either based on cross-sectional studies or longitudinal studies within a single company. Hence, it is difficult to transfer the results of this research as-is to a broader context, and thus, the external validity of individual research is limited unless additional efforts are taken to transfer the results to a broader context. Besides, it would be interesting to understand how technostress changes during the further course of the COVID-19-pandemic, to what extent there are habituation effects on the side of the employees or how job resources are successively provided to teleworking employees (e.g., where employees get additional IT equipment or managers manage their employees healthier due to the new experience).

One part of these limitations is addressed in Section 4.2, which examines the influence of personal factors (specifically the coping preference) in the work domain on employee health and productivity. However, there is potential for further research. We have used a cross-sectional study design to research coping as a moderator where relationships are based on the covariance analysis. It is important to note, therefore, that this does not involve causality. Causality can also flow the other way. For future research, we argue that coping is to be studied as a moderator—ideally to learn more about causality in long-term studies. The first evidence shows that causality flows both ways (Hauk et al. 2019). Furthermore, rather than actual coping actions, we have looked at coping strategies in general to draw broader findings. Although the distinction could already provide compelling contributions and implications, a differentiated consideration of coping strategies could lead to further insights. Finally, only one component, exhaustion, was the focus of our analyses. The disengagement of the behavior causes increased stress; in turn, a higher strain leads to an increased disengagement in the behavior at a later stage. It would be interesting for people who consume alcohol or other substances to get an insight into issues, such as the risk of addictions and the symptoms of depression, to overcome strained DTMs. Furthermore, other options may be considered, such as aspects of burnout, absence duration, or general health problems.

Designing DTMs that Foster the Reciprocal Interaction

Third, regarding the aim of Chapter 5 to develop frameworks and guidelines for DTMs that understand the social component and adjust accordingly to their user's needs, the results yield some technical, social, and ethical challenges which need to be addressed in future research. Beyond that, the research process also offers potential for improvement.

The research in Section 5.1 presented a generic medical sensor framework that can combine sensors and collect data independent of devices that build the ground for further research. Besides the one or other additional functionalities that would extend the applicability of the JDCF (e.g., first pre-processing of data, calculations of first aggregations, or conducting sensor fusion), the limitations refer to evaluation and relevance. The framework was implemented as a prototype and used for evaluation purposes in a laboratory experiment. During the game within our experiment, the sequence of stress levels always started with a low-arousal-mode followed by a high-arousal-mode with a repetition of both modes. To obtain a higher validity, it would have been better to avoid sequential effects in the experiment and, therefore, divide the participants in the laboratory study into two groups, one group starting with a low-arousal-mode and the other group starting with a high-arousal-mode. However, since the focus of the experiment was primarily on validating the framework's applicability and not on the stress measurement's accuracy and validity, this limitation is of less importance. Finally, it should be noted there are other frameworks for data processing besides ours. One example is the funf framework for collecting and analyzing mobile data developed by MIT Media Lab (Aharony et al. 2011). This framework uses the sensors integrated with the smartphone and stores the extracted data (e.g., GPS, call log, browser history). It prepares them for the user in the form of visualizations and reports. Another example is the Social Signal Interpretation framework from Wagner et al. (2013) that records, analyses, and recognizes human behavior (e.g., gestures, mimics, head nods, and emotional speech) by using data from cameras or microphones. Furthermore, there is a mobile version, which makes it possible to collect data outside of a laboratory setting (Damian et al. 2018). Although these frameworks bring their unique expertise to the field (funf for the processing of data from smartphones and the Social Signal Interpretation framework for the processing of multimedia data), we believe the development of the Java Data Collection Framework has been necessary to cover the breadth of relevant information related to stress (physiological, psychological and behavioral data about the user, data about the environment and data about the context).

Section 5.2 presented a DTM capable of assessing perceived stress using the Section 5.1 framework in a life-integrated and continual smartphone-based process. This prototype has shown the general feasibility and applicability of life-integrated mobile sensing to assess stress. Some aspects of the findings in this section require further testing and an extension of our results. Firstly, stress is a multi-faceted phenomenon, as already stated in several points in the dissertation. The ground truth of the developed prototype was perceived as stress, which is not necessarily the same as biological stress (Riedl 2013). Thus, going beyond perception towards physiological measurements will be a valuable addition to the present research. Second, our system relies on the regular usage of one primary smartphone. The exact boundaries of the scope are not yet clear. Future field experiments should measure smartphone usage intensity and recruit participants with diverse intensities to explore how intense smartphone interaction must be for reliable stress assessment. Thirdly, a technological solution for a perceived stress assessment is by no means intuitive, given that smartphones are potential stressors themselves (Lee et al. 2014). The subject of technostress and its effects on employees' health were discussed intensively over the course of the dissertation. Further research should investigate the paradox of how far a DTM can help with stress and also lead to technostress; therefore, doing more harm than good. Nonetheless, we argue that it is worth exploring and assessing how smartphone-based sensing can foster the development of innovative technologies that appropriately interact with a stressed or relaxed individual. Fourth, an evaluation involving the actual use of stress assessment in a realistic application context should be conducted. However, to achieve this, it is also necessary to increase the acceptance on the part of the users and motivate them to continue using this DTM. Fifth, refined statistical models or aggregation may improve model performance. For example, future research could investigate what amount of historical sensor data is best suited to predict stress. Besides, the value of customized models is worth exploring. For new users, stress assessment could initially be based on a pre-trained general model as presented in Section 5.2; the model could then be improved over time by customization, similar to the approach used by Rachuri et al. (2010) for personalized emotional detection. Finally, future work should link stress assessment to stress management interventions.

Research activities in Section 5.3 consolidated extant design knowledge formerly dispersed across various studies on mobile stress assessment and derived design requirements, an abstract blueprint, design principles, and design features. Furthermore, trade-offs between design requirements and the design features have been found by developing five prototypes. Nevertheless, research in Section 5.3 subject to some limitations. First, it is by no means clear that a technological solution for stress assessment is the most appropriate solution because technology itself is a potential stressor (Lee et al. 2014). Nevertheless, we contend that it is worth exploring and evaluating how mobile sensing and assessment can support stress management. Also, the assessment of stress using mobile sensors is subject to biological and sensory blurriness. Therefore, it might not be the right approach or associated with high costs in applications that depend on a very high accuracy of stress assessment, such as in medical applications. Furthermore, although 136 studies are already a substantial amount, we did not yet search in all outlets of IS and adjacent disciplines, which might reveal additional insights into best practices in MSA design. Lastly, the trade-offs were derived from the insights during the development of five prototypes, although we did not prototypically instantiate every single archetype. Furthermore, the range of possible uses of MSA is very broad, and therefore, our five prototypes can only address a small subset. Nevertheless, these five prototypes have already provided valuable insights that can support future researchers and users in the design of MSAs.

Understanding the Future Misfit

Lastly, regarding the aim of Chapter 6 to understand the upcoming misfit within the socio-technical system due to ongoing digitalization, the research results are accompanied by limitations in terms of methodological procedure and interpretability.

First, our sample in the qualitative study is not representative for all employees. Although we collected qualitative data of 61 individuals in expert interviews and focus groups, we did not select the individuals to be representative of the German workforce according to, for example, gender, age, or industry. However, by following a mixed-methods approach and combining the qualitative strand with a quantitative one, we were able to overcome this issue by testing our qualitative results in large-scale quantitative analysis. Second, we collected the quantitative data with the help of online surveys providing financial incentives. Typical weaknesses of this method, such as self-selection of the population, non-response, and questionable reliability of expressed opinions (Nayak and Narayan 2019), have to be considered in our research. Third, our three newly created dimensions non-availability, lacking sense of achievement, and performance control were tested with multiple large data sets, but only with employees in Germany. Future work may validate our results in other economic and cultural backgrounds. Fourth, it was tough to interpret the higher-order factor impediment. Therefore, future work needs to test these higher-order factor analyses with a different data set to check for stability and consistency and different potential compositions of higher-order factors. Fifth and last, we embedded our factors in a nomological net with job satisfaction and productivity. Future research should consider them with regard to potential antecedents (e.g., use or characteristics of digital technologies), further consequences (e.g., appraisal, coping behavior), or moderators (e.g., resources such as individual characteristics).

Future Research

Overall, besides the aforementioned limitations, this dissertation contributes to the IS community's knowledge base by providing knowledge regarding the interaction between employees and their digital workplace to foster the achievement of humanistic and instrumental objectives. Although the conducting of behavioral science and design science research added relevant and new descriptive and prescriptive knowledge to the existing knowledge base, further research is needed to achieve a healthy digital workplace.

On the one hand, a large part of the studies, both in the literature and the research presented in this dissertation, are based either on data from cross-sectional surveys or on data from a narrow context (for example, the employees of a single company). This is illustrated by the recently published article from Benlian (2020), who reviewed the "basket of eight" for empirical studies on technostress and found that almost exclusively cross-sectional surveys and a few isolated experiments were used as the research methodology. Accordingly, it is difficult to transfer the results as-is to a broader context, and thus, the external validity of individual research activity is limited unless additional efforts are taken to transfer the results to a broader context. Furthermore, in many cases, the participants for cross-sectional surveys are acquired via service providers or platforms like market research companies or crowdsourcing marketplace, where participants are paid an incentive. Many publications have already discussed the quality of this kind of data, and most of them conclude the data quality is similar to traditional paper-pencil questionnaires or self-acquired participants (Buhrmester et al. 2016; Kees et al. 2017; Peer et al. 2014). However, especially concerning the challenges of digitalization, this form of online data acquisition requires particular caution since the participants in the surveys themselves already have an affinity for the use of DTM. Accordingly, a higher digital competence, or at least a higher confidence in dealing with DTM, which has already been identified in several studies as a significant influence on the perception and further processing of technostress, is likely to be expected in the sample collected in an online survey. Therefore, further research should investigate the relationship between using an online survey and the observed digital stress by conducting larger-scale studies across several companies. In parallel, the use of a traditional paper-pencil method could provide further compelling insights in this regard. One final point to mention is the aspect of causality. Causality is not necessarily observable (Hume 2003). In fact, an observed correlation between events should not be considered causal until there are theory-based hypotheses. Furthermore, the correlation between cause and effect can be interpreted as causal if three criteria are met. There is a statistical relationship between the cause and the effect (first criterion), whereby the cause precedes the effect in time (second criterion). In addition, the statistical relationship between cause and effect must not disappear when other aspects that precede both the effect and the cause are considered (third criterion) (Hirschi and Selvin 2017; Lazarsfeld 1955; Price 1956). Accordingly, in cross-sectional studies, it is difficult to interpret observed relationships as causal, as only the first criteria and to a certain degree the second criteria can be addressed. Therefore, further longitudinal studies are necessary, especially when considering the consequences of digital stress, to obtain well-founded conclusions (Rindfleisch et al. 2008) as they are compared to cross-sectional studies more suitable to adequately address the second criterion. However, it is important to note that longitudinal studies are also not capable of proving or observing causality. However, there may be other confounding factors that can explain the changes in digital stress over time (i.e., the third criteria). For example, the change in digital stress in response to the COVID-19 pandemic of Section 4.1 may not only be explained by self-efficacy but perhaps even more by the actual digital competence that, for example, is built up in the course of training and routine, which, in turn, leads to higher self-efficacy. Accordingly, future longitudinal studies should take up the advantages of a mixed-method design and, in addition to quantitative analyses, also carry out qualitative analyses, such as in the form of interviews to better understand the results.

On the other hand, this dissertation's research has identified measures along with the three levers of technology, organization, and individual that support the design of a healthy digital workplace. However, these measures have not yet been examined concerning their actual effectiveness in companies. Therefore, in the further course of the research, specific measures should be implemented in companies and their effectiveness observed. A procedure based on action research is suitable for solving current practical problems while expanding scientific knowledge and involving researchers and subjects (Babüroglu and Ravn 1992). Action research is typically conducted in an iterative process, which is said to improve the practical relevance of IS research. This process consists of two steps. The first step refers to an analysis of the subject's social situation by the researcher, and then in the second step, changes are introduced and the effects are studied (Blum 1998). The measures should be introduced and evaluated in various companies to transfer the results to a broader context. A multiple case study that "explores [...] real-life, contemporary [...] multiple [...] cases over time, through detailed, in-depth data collection involving multiple sources of information" (Creswell and Poth 2016, p. 97) could be used for this purpose. A multiple case study would enable us to understand the similarities and differences between the effects of countermeasures targeting digital stress applied in multiple organizations (Baxter and Jack 2008) by analyzing data both within each organization and across different organizations (Yin 2017).

Lastly, the DTM for assessing stress developed in Chapter 5 is the fundamental prerequisite for using DTM to support employees and individuals in dealing with stress. However, the assessment of stress alone is not sufficient. Instead, it is necessary to develop additional components to achieve the original goal of the proposed DTM that adjusts accordingly to the users' needs. The first step on this path could be, for example, to prepare the data in a kind of diary to support users in self-reflection before the DTM itself takes measures to deal with stress in a later version. For this purpose, it will first be necessary to conduct further research on which individual and context-specific information influences the choice of a measure for dealing with stress to develop possible data-driven models to identify measures. This will ultimately enable the development of individual stress management DTMs, enable adaptive user interaction in an enterprise context, and even allow the design of adaptive enterprise DTMs (Adam et al. 2017).

8. Conclusion

This research in this dissertation supports the successful change toward a healthy digital workplace in the face of digitalization. It tackles one of the most significant socio-technical challenges of modern humankind. Although much descriptive knowledge about the reciprocal interaction between the social component and technical component was acquired and supplemented by prescriptive knowledge about the design of the individual components, this is only the first step on the way to a healthy digital workplace.

For this, companies and also employees must be prepared to adapt to the changed situation through digitalization, because according to Charles Darwin (Megginson 1963, p. 4), "it is not the strongest of the species that survives, nor the most intelligent that survives. It is the one that is the most adaptable to change". Just how valid this assessment from a completely different context is can be seen from the many well-known companies (e.g., Kodak, Quelle, Nokia) that have not managed to keep up with the changes brought about by digitalization. It is important to bear in mind that digitalization is not just purely technical development. Instead, through modern DTMs, there is a change in communication and collaboration between employees, which changes the work's nature. Accordingly, the focus should be on both DTMs and employees as users, in line with the core of IS. After all, the goal of DTM as a technical component is to solve problems, support the achievement of goals, or generally serve a purpose that is human-defined (Lee et al. 2015). At the same time, however, companies must also create suitable conditions for using these DTMs and support employees in developing the necessary skills and attitudes in dealing with DTMs. Thus, it is essential to bring together and promote the proper well-designed DTMs, suitable working conditions, and the necessary knowledge in dealing with DTMs to achieve a healthy digital workplace. This dissertation would like to contribute to this and concludes with a statement from Steve Jobs from 1994, one of the founders of Apple that is one of the most innovative tech companies (Ringel et al. 2020), who argues that "technology is nothing. What's important is that you have faith in people, that they're basically good and smart - and if you give them tools, they'll do wonderful things with them" (Goodell 1994).

References

Aamodt, M. 2012. *Industrial/Organizational Psychology: An Applied Approach*, Belmont, CA: Wadsworth Publishing.

Adam, M. T. P., Gimpel, H., Maedche, A., and Riedl, R. 2014. "Stress-Sensitive Adaptive Enterprise Systems:Theoretical Foundations and Design Blueprint," in *Proceedings of the Gmunden Retreat on NeuroIS*, pp. 39-41.

Adam, M. T. P., Gimpel, H., Maedche, A., and Riedl, R. 2017. "Design Blueprint for Stress-Sensitive Adaptive Enterprise Systems," *Business & Information Systems Engineering* (59:4), pp. 277-291 (doi: 10.1007/s12599-016-0451-3).

Adams, P., Rabbi, M., Rahman, T., Matthews, M., Voida, A., Gay, G., Choudhury, T., and Voida, S. 2014. "Towards Personal Stress Informatics: Comparing Minimally Invasive Techniques for Measuring Daily Stress in the Wild," in *Proceedings of the International Conference on Pervasive Computing Technologies for Healthcare*, pp. 72-79.

Adnane, M., Jiang, Z., Mori, N., and Matsumoto, Y. 2011. "An automated program for mental stress and apnea/hypopnea events detection," in *7th International Workshop on Systems, Signal Processing and Their Applications (WoSSPA), 2011*: *9 - 11 May 2011, Come d'Or, Tipaza, Algeria*, Tipaza, Algeria. 5/9/2011 - 5/11/2011, Piscataway, NJ: IEEE, pp. 59-62.

Afreen, R. 2014. "Bring your own device (BYOD) in higher education: Opportunities and challenges," *International Journal of Emerging Trends & Technology in Computer Science* (3:1), pp. 233-236.

Agarwal, and Lucas 2005. "The Information Systems Identity Crisis: Focusing on High-Visibility and High-Impact Research," *MIS Quarterly* (29:3), p. 381 (doi: 10.2307/25148689).

Ågerfalk, P. J. 2014. "Insufficient theoretical contribution: a conclusive rationale for rejection?" *European Journal of Information Systems* (23:6), pp. 593-599 (doi: 10.1057/ejis.2014.35).

Agho, A. O., Price, J. L., and Mueller, C. W. 1992. "Discriminant validity of measures of job satisfaction, positive affectivity and negative affectivity," *Journal of Occupational and Organizational Psychology* (65:3), pp. 185-195 (doi: 10.1111/J.2044-8325.1992.TB00496.X).

Aharony, N., Pan, W., Ip, C., Khayal, I., and Pentland, A. 2011. "Social fMRI: Investigating and shaping social mechanisms in the real world," *Pervasive and Mobile Computing* (7:6), pp. 643-659 (doi: 10.1016/j.pmcj.2011.09.004).

Ahmed, B., Khan, H. M., Choi, J., and Gutierrez-Osuna, R. 2016. "ReBreathe: A Calibration Protocol that Improves Stress/Relax Classification by Relabeling Deep Breathing Relaxation Exercises," *IEEE Transactions on Affective Computing* (7:2), pp. 150-161 (doi: 10.1109/TAFFC.2015.2459682).

Aigrain, J. 2016. *Multimodal Detection of Stress: Evaluation of the Impact of Several Assessment Strategies*.

Akbari, E., Pilot, A., and Robert-Jan Simons, P. 2015. "Autonomy, competence, and relatedness in foreign language learning through Facebook," *Computers in Human Behavior* (48), pp. 126-134 (doi: 10.1016/j.chb.2015.01.036).

Albu, A. B., Widsten, B., Wang, T., Lan, J., and Mah, J. 2008. "A computer vision-based system for real-time detection of sleep onset in fatigued drivers," in *IEEE Intelligent Vehicles Symposium, 2008*: *Eindhoven, Netherlands, 4 - 6 June 2008,* Eindhoven, Netherlands. 6/4/2008 - 6/6/2008, Piscataway, NJ: IEEE Service Center, pp. 25-30.

Alemdar, H., and Ersoy, C. 2010. "Wireless sensor networks for healthcare: A survey," *Computer networks* (54:15), pp. 2688-2710 (doi: 10.1016/j.comnet.2010.05.003).

Alpaydin, E. 2004. *Introduction to machine learning*, Cambridge, Mass.: MIT Press.

Ângelo, R. P., and Chambel, M. J. 2014. "The role of proactive coping in the Job Demands–Resources Model: A cross-section study with firefighters," *European Journal of Work and Organizational Psychology* (23:2), pp. 203-216 (doi: 10.1080/1359432X.2012.728701).

Arnetz, B. B., and Wiholm, C. 1997. "Technological stress: Psychophysiological symptoms in modern offices," *Journal of Psychosomatic Research* (43:1), pp. 35-42 (doi: 10.1016/s0022-3999(97)00083-4).

Ashill, N. J., Rod, M., and Gibbs, T. 2015. "Coping with stress: A study of retail banking service workers in Russia," *Journal of Retailing and Consumer Services* (23), pp. 58-69 (doi: 10.1016/j.jretconser.2014.12.006).

Ashok, C. K., Karunanidhi, S., and Narayanan, R. 2016. "Validation of Stress Assessment using Mobile Phone," *Journal of Psychosocial Research* (11:2), pp. 479-488.

Astor, P. J., Adam, M. T. P., Jerčić, P., Schaaff, K., and Weinhardt, C. 2013. "Integrating Biosignals into Information Systems: A NeuroIS Tool for Improving Emotion Regulation," *Journal of Management Information Systems* (30:3), pp. 247-278 (doi: 10.2753/MIS0742-1222300309).

Atanasoff, L., and Venable, M. A. 2017. “Technostress: Implications for Adults in the Workforce,” *The Career Development Quarterly* (65:4), pp. 326-338 (doi: 10.1002/cdq.12111).

Attaran, M., Attaran, S., and Kirkland, D. 2019. “The Need for Digital Workplace,” *International Journal of Enterprise Information Systems* (15:1), pp. 1-23 (doi: 10.4018/IJEIS.2019010101).

Attaran, N., Brooks, J., and Mohsenin, T. 2016. “A low-power multi-physiological monitoring processor for stress detection,” in *IEEE SENSORS 2016*: *Orlando, Florida, USA, October 30-November 2, 2016 : 2016 proceedings papers.* 2016/10, New York: IEEE, pp. 1-3.

Ayyagari, Grover, and Purvis 2011. “Technostress: Technological Antecedents and Implications,” *MIS Quarterly* (35:4), p. 831 (doi: 10.2307/41409963).

Ayzenberg, Y., Hernandez Rivera, J., and Picard, R. 2012. “FEEL,” in *Proceeding of Extended Abstracts on Human Factors in Computing System*, p. 2357.

Babüroglu, O. N., and Ravn, I. 1992. “Normative Action Research,” *Organization Studies* (13:1), pp. 19-34 (doi: 10.1177/017084069201300104).

Bacharach, S. B., Bamberger, P., and Conley, S. 1991. “Work-home conflict among nurses and engineers: Mediating the impact of role stress on burnout and satisfaction at work,” *Journal of Organizational Behavior* (12:1), pp. 39-53 (doi: 10.1002/job.4030120104).

Bahadur, P., and Yadav, D. S. 2015. “Computer forensics-digitized science,” in *2015 SAI Intelligent Systems Conference (IntelliSys)*: *10-11 Nov. 2015*, London, United Kingdom. 11/10/2015 - 11/11/2015, Piscataway, NJ: IEEE, pp. 1025-1031.

Bailey, D. E., and Kurland, N. B. 2002. “A review of telework research: findings, new directions, and lessons for the study of modern work,” *Journal of Organizational Behavior* (23:4), pp. 383-400 (doi: 10.1002/job.144).

Bakker, A. B., and Demerouti, E. 2007. “The Job Demands-Resources model: state of the art,” *Journal of Managerial Psychology* (22:3), pp. 309-328 (doi: 10.1108/02683940710733115).

Bakker, A. B., and Demerouti, E. 2017. “Job demands-resources theory: Taking stock and looking forward,” *Journal of occupational health psychology* (22:3), pp. 273-285 (doi: 10.1037/ocp0000056).

Bakker, A. B., and Schaufeli, W. B. 2008. “Positive organizational behavior: engaged employees in flourishing organizations,” *Journal of Organizational Behavior* (29:2), pp. 147-154 (doi: 10.1002/job.515).

Bakker, J., Pechenizkiy, M., and Sidorova, N. 2011. “What's Your Current Stress Level? Detection of Stress Patterns from GSR Sensor Data,” Proceedings of the IEEE International Conference on Data Mining Workshops, pp. 573-580.

Banville, C., and Landry, M. 1989. “Can the field of MIS be disciplined?” *Communications of the ACM* (32:1), pp. 48-60 (doi: 10.1145/63238.63241).

Barber, L. K., Conlin, A. L., and Santuzzi, A. M. 2019. “Workplace telepressure and work-life balance outcomes: The role of work recovery experiences,” *Stress and Health: Journal of the International Society for the Investigation of Stress* (35:3), pp. 350-362 (doi: 10.1002/smi.2864).

Barley, S. R., Bechky, B. A., and Milliken, F. J. 2017. “The Changing Nature of Work: Careers, Identities, and Work Lives in the 21 st Century,” *Academy of Management Discoveries* (3:2), pp. 111-115 (doi: 10.5465/amd.2017.0034).

Barrett, P. 2007. “Structural equation modelling: Adjudging model fit,” *Personality and Individual Differences* (42:5), pp. 815-824 (doi: 10.1016/j.paid.2006.09.018).

Bauer, G., and Lukowicz, P. 2012. “Can smartphones detect stress-related changes in the behaviour of individuals?” in *2012 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, Lugano, Switzerland, pp. 423-426.

Baxter, P., and Jack, S. 2008. “Qualitative case study methodology: Study design and implementation for novice researchers,” *The qualitative report* (13:4), pp. 544-559.

Beath, C., Berente, N., Gallivan, M., and Lyytinen, K. 2013. “Expanding the Frontiers of Information Systems Research: Introduction to the Special Issue,” *Journal of the Association for Information Systems* (14:4), !-XVI (doi: 10.17705/1jais.00330).

Beaton, D., Bombardier, C., Guillemin, F., and Ferraz, M. B. 2002. “Recommendations for the cross-cultural adaptation of health status measures,” *New York: American Academy of Orthopaedic Surgeons* (12), pp. 1-9.

Becker, J., Berger, M., Gimpel, H., Lanzl, J., and Regal, C. 2020a. “Considering Characteristic Profiles of Technologies at the Digital Workplace : The Influence on Technostress,” in *41st International Conference on Information Systems (ICIS)*.

Becker, J., Derra, N. D., Regal, C., and Kühlmann, T. M. 2020b. “Mitigating Technostress - The Moderating Effect of Functional and Dysfunctional Coping,” *Working Paper*.

Beckmann, S., Lahmer, S., Markgraf, M., Meindl, O., Rauscher, J., Regal, C., Gimpel, H., and Bauer, B. 2017. “Generic sensor framework enabling personalized healthcare,” in *IEEE Life Sciences Conference (LSC)*, pp. 83-86.

Ben-Hur, A., and Weston, J. 2010. “A user's guide to support vector machines,” *Methods in molecular biology* (609), pp. 223-239 (doi: 10.1007/978-1-60327-241-4_13).

Benlian, A. 2020. “A Daily Field Investigation of Technology-Driven Spillovers from Work to Home,” *Management Information Systems Quarterly* (44:3), pp. 1259-1300 (doi: 10.25300/MISQ/2020/14911).

Benson, H. J. 2002. *Mic robiological Applioations*, The McGraw− Hill Companies.

Berger, S., Denner, M.-S., and Röglinger, M. 2018. “The Nature of Digital Technologies: Development of a Multi-Layer Taxonomy,” in *26th European Conference on Information Systems (ECIS)*.

Bernaards, C. A., and Jennrich, R. I. 2005. “Gradient Projection Algorithms and Software for Arbitrary Rotation Criteria in Factor Analysis,” *Educational and Psychological Measurement* (65:5), pp. 676-696 (doi: 10.1177/0013164404272507).

Berndt, R.-D., Takenga, M. C., Kuehn, S., Preik, P., Stoll, N., Thurow, K., Kumar, M., Weippert, M., Rieger, A., and Stoll, R. 2011. “A scalable and secure Telematics Platform for the hosting of telemedical applications. Case study of a stress and fitness monitoring,” in *13th IEEE International Conference on e-Health Networking, Applications and Services (Healthcom), 2011*: *13 - 15 June 2011, Columbia, Missouri, USA*, Columbia, MO, USA. 6/13/2011 - 6/15/2011, Piscataway, NJ: IEEE, pp. 118-121.

Best, S. J., Krueger, B. S., and Ladewig, J. 2006. “Privacy in the information age,” *International Journal of Public Opinion Quarterly* (70:3), pp. 375-401.

Betti, S., Lova, R. M., Rovini, E., Acerbi, G., Santarelli, L., Cabiati, M., Del Ry, S., and Cavallo, F. 2018. “Evaluation of an Integrated System of Wearable Physiological Sensors for Stress Monitoring in Working Environments by Using Biological Markers,” *IEEE Transactions on Biomedical Engineering* (65:8), pp. 1748-1758 (doi: 10.1109/TBME.2017.2764507).

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., and Venkatraman, N. 2013. “Digital Business Strategy: Toward a Next Generation of Insights,” *MIS Quarterly* (37:2), pp. 471-482 (doi: 10.25300/MISQ/2013/37:2.3).

Bharadwaj, A. S. 2000. "A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation," *MIS Quarterly* (24:1), p. 169 (doi: 10.2307/3250983).

Bhattacherjee, A. 2012. "Social science research: Principles, methods, and practices," Global Text Project.

Blum, A. 1998. *On-line algorithms in machine learning*, Springer.

Boateng, G., and Kotz, D. 2016. "StressAware: An app for real-time stress monitoring on the amulet wearable platform," in *URTC*: *2016 IEEE MIT Undergraduate Research Technology Conference : Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA, USA, November 4-6 2016.* 2016/11, New York: IEEE, pp. 1-4.

Boersma, S. N., Maes, S., Joekes, K., and Dusseldorp, E. 2006. "Goal processes in relation to goal attainment: predicting health-related quality of life in myocardial infarction patients: Predicting health-related quality of life in myocardial infarction patients," *Journal of health psychology* (11:6), pp. 927-941 (doi: 10.1177/1359105306069095).

Bogomolov, A., Lepri, B., Ferron, M., Pianesi, F., and Pentland, A. 2014. "Daily Stress Recognition from Mobile Phone Data, Weather Conditions and Individual Traits," in *Proceedings of the ACM International Conference on Multimedia*, Orlando, Florida, USA, pp. 477-486.

Bolger, N. 1990. "Coping as a personality process: A prospective study," *Journal of personality and social psychology* (59:3), pp. 525-537 (doi: 10.1037//0022-3514.59.3.525).

Bondanini, G., Giorgi, G., Ariza-Montes, A., Vega-Muñoz, A., and Andreucci-Annunziata, P. 2020. "Technostress Dark Side of Technology in the Workplace: A Scientometric Analysis," *International Journal of Environmental Research and Public Health* (17:21) (doi: 10.3390/ijerph17218013).

Bonenberger, L., Gimpel, H., Regal, C., and Schmidt, M. 2020. "Design Theory for Mobile Stress Assessment Systems," *Working Paper*.

Bong, M., and Skaalvik, E. M. 2003. "Academic Self-Concept and Self-Efficacy: How Different are They Really?" *Educational psychology review* (15:1), pp. 1-40 (doi: 10.1023/A:1021302408382).

Boomsma, A. 1982. "The Robustness of LISREL Against Small Sample Sizes in Factor Analysis Models," *Systems Under Indirect Observation: Causality, Structure, Prediction*.

Bostrom, R. P., Gupta, S., and Thomas, D. 2009. “A Meta-Theory for Understanding Information Systems Within Sociotechnical Systems,” *Journal of Management Information Systems* (26:1), pp. 17-48 (doi: 10.2753/MIS0742-1222260102).

Bostrom, R. P., and Heinen, J. S. 1977a. “MIS Problems and Failures: A Socio-Technical Perspective, Part II: The Application of Socio-Technical Theory,” *MIS Quarterly* (1:4), p. 11 (doi: 10.2307/249019).

Bostrom, R. P., and Heinen, J. S. 1977b. “MIS Problems and Failures: A Socio-Technical Perspective. Part I: The Causes,” *MIS Quarterly* (1:3), p. 17 (doi: 10.2307/248710).

Botella, C., Riva, G., Gaggioli, A., Wiederhold, B. K., Alcaniz, M., and Baños, R. M. 2012. “The present and future of positive technologies,” *Cyberpsychology, behavior and social networking* (15:2), pp. 78-84 (doi: 10.1089/cyber.2011.0140).

Boucsein, W. 2009. “Forty Years of Research on System Response Times – What Did We Learn from It?” in *Industrial Engineering and Ergonomics*: *Visions, Concepts, Methods and Tools*, C. Schlick (ed.), Berlin: Springer, pp. 575-593.

Braukmann, J., Schmitt, A., Ďuranová, L., and Ohly, S. 2018. “Identifying ICT-Related Affective Events Across Life Domains and Examining their Unique Relationships with Employee Recovery,” *Journal of Business and Psychology* (33:4), pp. 529-544 (doi: 10.1007/s10869-017-9508-7).

Braun, V., and Clarke, V. 2006. “Using thematic analysis in psychology,” *Qualitative research in psychology* (3:2), pp. 77-101.

Brod, C. 1982. “Managing Technostress: Optimizing the Use of Computer Technology,” *Personnel Journal* (61:10), pp. 753-757.

Brod, C. 1984. *Technostress*: *The Human Cost of the Computer Revolution*, Reading, Mass.: Addison-Wesley.

Brummelhuis, L. L. ten, and Bakker, A. B. 2012. “A resource perspective on the work-home interface: the work-home resources model,” *The American psychologist* (67:7), pp. 545-556 (doi: 10.1037/a0027974).

Brunstein, J. C. 1993. “Personal goals and subjective well-being: A longitudinal study,” *Journal of personality and social psychology* (65:5), pp. 1061-1070 (doi: 10.1037/0022-3514.65.5.1061).

Buchwald, A., Letner, A., Urbach, N., and Entreß-Fürsteneck, M. v. 2018. “Insights into Personal ICT Use: Understanding continuance and Discontinuance of Wearable Self-tracking Devices,” in *26th European Conference on Information Systems (ECIS)*, p. 37.

Buchwald, A., Letner, A., Urbach, N., and von Entreß-Fürsteneck, M. 2015. "Towards Explaining the Use of Self-Tracking Devices: Conceptual Development of a Continuance and Discontinuance Model," in *36th International Conference on Information Systems*.

Buhrmester, M., Kwang, T., and Gosling, S. D. 2016. "Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality data?" in *Methodological issues and strategies in clinical research (4th ed.),* A. E. Kazdin (ed.), Washington: American Psychological Association, pp. 133-139.

Burr, H., Berthelsen, H., Moncada, S., Nübling, M., Dupret, E., Demiral, Y., Oudyk, J., Kristensen, T. S., Llorens, C., Navarro, A., Lincke, H.-J., Bocéréan, C., Sahan, C., Smith, P., and Pohrt, A. 2019. "The Third Version of the Copenhagen Psychosocial Questionnaire," *Safety and Health at Work* (10:4), pp. 482-503 (doi: 10.1016/j.shaw.2019.10.002).

Califf, C. B., Sarker, S., and Sarker, S. 2020. "The bright and dark sides of technostress: A mixed-methods study involving healthcare IT," *MIS Quarterly* (44:2), pp. 809-856 (doi: 10.25300/MISQ/2020/14818).

Carpenter, R. 2016. "A Review of Instruments on Cognitive Appraisal of Stress," *Archives of Psychiatric Nursing* (30:2), pp. 271-279 (doi: 10.1016/j.apnu.2015.07.002).

Carver, C. S. 1997. "You want to measure coping but your protocol's too long: consider the brief COPE," *International Journal of Behavioral Medicine* (4:1), pp. 92-100 (doi: 10.1207/s15327558ijbm0401_6).

Carver, C. S., Scheier, M. F., and Weintraub, J. K. 1989. "Assessing coping strategies: A theoretically based approach," *Journal of personality and social psychology* (56:2), pp. 267-283 (doi: 10.1037//0022-3514.56.2.267).

Cassidy, K. W., Werner, R. S., Rourke, M., Zubernis, L. S., and Balaraman, G. 2003. "The Relationship Between Psychological Understanding and Positive Social Behaviors," *Social Development* (12:2), pp. 198-221 (doi: 10.1111/1467-9507.00229).

CDU, CSU & SPD 2018. "Ein neuer Aufbruch für Europa. Eine neue Dynamik für Deutschland. Ein neuer Zusammenhalt für unser Land: Koalitionsvertrag zwischen CDU, CSU und SPD," 19. Legislaturperiode, Berlin.

Cernat, R. A., Speriatu, A. M., Taralunga, D. D., Hurezeanu, B. E., Nicolae, I. E., Strungaru, R., and Ungureanu, G. M. 2017. "Stress influence on drivers identified by monitoring galvanic skin resistance and heart rate variability," in *2017 E-Health and Bioengineering*

Conference (EHB): *06/22/2017 to 06/24/2017, Sinaia, Romania*, E.-H. a. B. Conference (ed.). 2017/06, [Piscataway, NJ]: IEEE, pp. 261-264.

Chang, K., Fisher, D., Canny, J., and Hartmann, B. 2011. "How's My Mood and Stress?: An Efficient Speech Analysis Library for Unobtrusive Monitoring on Mobile Phones," in *Proceedings of the International Conference on Body Area Networks*, Beijing, China. 7-8 November 2011, pp. 71-77.

Charlesworth, A. 2009. "The ascent of smartphone," *Engineering & Technology* (4:3), pp. 32-33 (doi: 10.1049/et.2009.0306).

Chen, A., and Karahanna, E. 2014. "Boundaryless Technology: Understanding the Effects of Technology-Mediated Interruptions across the Boundaries between Work and Personal Life," *AIS Transactions on Human-Computer Interaction* (6:2), pp. 16-36 (doi: 10.17705/1THCI.00059).

Chen, J. V., Tran, A., and Nguyen, T. 2019. "Understanding the discontinuance behavior of mobile shoppers as a consequence of technostress: An application of the stress-coping theory," *Computers in Human Behavior* (95), pp. 83-93 (doi: 10.1016/j.chb.2019.01.022).

Chen, T., Yuen, P., Richardson, M., Liu, G., and She, Z. 2014. "Detection of Psychological Stress Using a Hyperspectral Imaging Technique," *IEEE Transactions on Affective Computing* (5:4), pp. 391-405 (doi: 10.1109/TAFFC.2014.2362513).

Cheung, G. W., and Rensvold, R. B. 2002. "Evaluating Goodness-of-Fit Indexes for Testing Measurement Invariance," *Structural Equation Modeling: A Multidisciplinary Journal* (9:2), pp. 233-255 (doi: 10.1207/S15328007SEM0902_5).

Chiappetta, M. 2017. "The Technostress: definition, symptoms and risk prevention," *Senses and Sciences* (4:1), pp. 358-361 (doi: 10.14616/sands-2017-1-358361).

Chiasson, and Davidson 2005. "Taking Industry Seriously in Information Systems Research," *MIS Quarterly* (29:4), p. 591 (doi: 10.2307/25148701).

Cho, Y., Bianchi-Berthouze, N., and Julier, S. J. 2017. "DeepBreath: Deep learning of breathing patterns for automatic stress recognition using low-cost thermal imaging in unconstrained settings," in *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*: *23-26 Oct. 2017*, I. C. o. A. C. a. I. Interaction (ed.). 2017/10, [Piscataway, NJ]: IEEE, pp. 456-463.

Choudhury, T., Borriello, G., Consolvo, S., Haehnel, D., Harrison, B., Hemingway, B., Hightower, J., Klasnja, P. "., Koscher, K., LaMarca, A., Landay, J. A., LeGrand, L., Lester, J., Rahimi, A., Rea, A., and Wyatt, D. 2008. "The Mobile Sensing Platform: An

Embedded Activity Recognition System," *IEEE Pervasive Computing* (7:2), pp. 32-41 (doi: 10.1109/MPRV.2008.39).

Christ-Brendemühl, S., and Schaarschmidt, M. 2020. "The impact of service employees' technostress on customer satisfaction and delight: A dyadic analysis," *Journal of Business Research* (117), pp. 378-388 (doi: 10.1016/j.jbusres.2020.06.021).

Ciman, M., and Wac, K. 2018. "Individuals' Stress Assessment Using Human-Smartphone Interaction Analysis," *IEEE Transactions on Affective Computing* (9:1), pp. 51-65 (doi: 10.1109/TAFFC.2016.2592504).

Ciman, M., Wac, K., and Gaggi, O. 2015. "iSenseStress: Assessing stress through human-smartphone interaction analysis," (doi: 10.4108/icst.pervasivehealth.2015.259280).

Cohen, S. 2010. *Dr. Cohen's Scales*. http://www.psy.cmu.edu/~scohen/scales. Accessed 30 March 2019.

Cohen, S., Kamarck, T., and Mermelstein, R. 1983. "A Global Measure of Perceived Stress," *Journal of Health and Social Behavior* (24:4), p. 385 (doi: 10.2307/2136404).

Cohen, S., and Williamson, G. M. 1988. "Perceived Stress in a Probability Sample of the United States," in *The social psychology of health*, S. Spacapan and S. Oskamp (eds.), Newbury Park: Sage.

Colbert, A., Yee, N., and George, G. 2016. "The Digital Workforce and the Workplace of the Future," *Academy of Management Journal* (59:3), pp. 731-739 (doi: 10.5465/amj.2016.4003).

Compeau, D. R., and Higgins, C. A. 1995. "Computer Self-Efficacy: Development of a Measure and Initial Test," *Management Information Systems Quarterly* (19:2), p. 189 (doi: 10.2307/249688).

Cooper, C. L. 2006. "The changing nature of work: workplace stress and strategies to deal with it," *Journal of Managerial Psychology* (97:2), pp. 132-136.

Cooper, C. L., and Cartwright, S. 1994. "Healthy Mind; Healthy Organization— A Proactive Approach to Occupational Stress," *Human Relations* (47:4), pp. 455-471 (doi: 10.1177/001872679404700405).

Cooper, C. L., Dewe, P., and O'Driscoll, M. P. 2001. *Organizational Stress*: *A Review and Critique of Theory, Research, and Applications*, Thousand Oaks, CA: SAGE Publications.

Corbin, J., and Strauss, A. 2014. *Basics of qualitative research: Techniques and procedures for developing grounded theory*, California: SAGE Publications.

Costin, R., Rotariu, C., and Pasarica, A. 2012. “Mental stress detection using heart rate variability and morphologic variability of EeG signals,” in *International Conference and Exposition on Electrical and Power Engineering (EPE), 2012*: *7th edition ; 25 - 27 Oct. 2012, Iasi, Romania ; [including workshop papers],* Iasi. 10/25/2012 - 10/27/2012, Piscataway, NJ: IEEE, pp. 591-596.

Couderc, P., and Kermarrec, A.-M. 1999. “Improving Level of Service for Mobile Users Using Context-Awareness,” in *Proceedings of the 18th IEEE Symposium on Reliable Distributed Systems*, IEEE Computer Society, p. 24.

Creswell, J. W. 2014. *A concise introduction to mixed methods research*, SAGE Publications.

Creswell, J. W., and Poth, C. N. 2016. *Qualitative inquiry and research design: Choosing among five approaches*, SAGE Publications.

CRONBACH, L. J., and MEEHL, P. E. 1955. “Construct validity in psychological tests,” *Psychological Bulletin* (52:4), pp. 281-302 (doi: 10.1037/h0040957).

Dahlan, M. K. M., Abdullah, N., and Suhaimi, A. I. H. 2018. “A Study on Supporting Factors of Digital Workplace Diffusion in Public Sector,” in *International Conference on User Science and Engineering*, Singapore: Springer, pp. 327-335.

Damian, I., Dietz, M., and André, E. 2018. “The SSJ Framework: Augmenting Social Interactions Using Mobile Signal Processing and Live Feedback,” *Frontiers in ICT* (5), p. 13 (doi: 10.3389/fict.2018.00013).

Dardas, L. A., and Ahmad, M. M. 2015. “Coping strategies as mediators and moderators between stress and quality of life among parents of children with autistic disorder,” *Stress and Health* (31:1), pp. 5-12 (doi: 10.1002/smi.2513).

Davis, G. B. 2002. “Anytime/anyplace computing and the future of knowledge work,” *Communications of the ACM* (45:12), pp. 67-73 (doi: 10.1145/585597.585617).

Day, A., Paquet, S., Scott, N., and Hambley, L. 2012. “Perceived information and communication technology (ICT) demands on employee outcomes: the moderating effect of organizational ICT support,” *Journal of occupational health psychology* (17:4), pp. 473-491 (doi: 10.1037/a0029837).

Day, A., Scott, N., and Kevin Kelloway, E. 2020. “Information and communication technology: Implications for job stress and employee well-being,” in *Entrepreneurial and Small Business Stressors, Experienced Stress, and Well-Being*, P. L. Perrewé, P. D. Harms and C.-H. Chang (eds.), Emerald Publishing Limited, pp. 317-350.

Demerouti, E., and Bakker, A. B. 2011. "The Job Demands–Resources model: Challenges for future research," *SA Journal of Industrial Psychology* (37:2), Art. #974 1–9 (doi: 10.4102/sajip.v37i2.974).

Demerouti, E., Bakker, A. B., Nachreiner, F., and Schaufeli, W. B. 2001. "The job demands-resources model of burnout," *The Journal of applied psychology* (86:3), pp. 499-512 (doi: 10.1037//0021-9010.86.3.499).

Demerouti, E., Mostert, K., and Bakker, A. B. 2010. "Burnout and work engagement: a thorough investigation of the independency of both constructs," *Journal of occupational health psychology* (15:3), pp. 209-222 (doi: 10.1037/a0019408).

Dery, K., Sebastian, I. M., and van der Meulen, N. 2017. "The Digital Workplace is Key to Digital Innovation," *MIS Quarterly Executive* (16:2).

DeSanctis, G., and Poole, M. S. 1994. "Capturing the Complexity in Advanced Technology Use: Adaptive Structuration Theory," *Organization science* (5:2), pp. 121-147 (doi: 10.1287/orsc.5.2.121).

Dettmers, J., Vahle-Hinz, T., Bamberg, E., Friedrich, N., and Keller, M. 2016. "Extended work availability and its relation with start-of-day mood and cortisol," *Journal of occupational health psychology* (21:1), pp. 105-118 (doi: 10.1037/a0039602).

Deutscher Gewerkschaftsbund 2019. *Erfolge der Gewerkschaften im Spiegel der Maiplakate*: *Historische Erfolge und Errungenschaften der Gewerkschaften für die Beschäftigten im Spiegel von Gewerkschafts- und Mai-Plakaten*. https://www.dgb.de/themen/++co++d3afa698-d3ba-11e4-b7f0-52540023ef1a#arbeitsschutz. Accessed 16 November 2020.

Devereux, J. M., Hastings, R. P., Noone, S. J., Firth, A., and Totsika, V. 2009. "Social support and coping as mediators or moderators of the impact of work stressors on burnout in intellectual disability support staff," *Research in developmental disabilities* (30:2), pp. 367-377 (doi: 10.1016/j.ridd.2008.07.002).

Dey, A. K. 2016. "Context-aware computing," in *Ubiquitous computing fundamentals*, J. Krumm (ed.), Chapman and Hall/CRC, pp. 321-352.

Dey, A. K., Abowd, G. D., and Salber, D. 2001. "A Conceptual Framework and a Toolkit for Supporting the Rapid Prototyping of Context-Aware Applications," *Human–Computer Interaction* (16:2-4), pp. 97-166 (doi: 10.1207/S15327051HCI16234_02).

Dickerson, S. S., and Kemeny, M. E. 2004. “Acute stressors and cortisol responses: a theoretical integration and synthesis of laboratory research,” *Psychological Bulletin* (130:3), pp. 355-391 (doi: 10.1037/0033-2909.130.3.355).

Diener, E., Lucas, R. E., and Scollon, C. N. 2006. “Beyond the hedonic treadmill: revising the adaptation theory of well-being,” *The American psychologist* (61:4), pp. 305-314 (doi: 10.1037/0003-066X.61.4.305).

Dimoka, A., Pavlou, P. A., and Davis, F. D. 2011. “Research Commentary —NeuroIS: The Potential of Cognitive Neuroscience for Information Systems Research,” *Information Systems Research* (22:4), pp. 687-702 (doi: 10.1287/isre.1100.0284).

Dobbins, C., and Fairclough, S. 2019. “Signal Processing of Multimodal Mobile Lifelogging Data Towards Detecting Stress in Real-World Driving,” *IEEE Transactions on Mobile Computing* (18:3), pp. 632-644 (doi: 10.1109/TMC.2018.2840153).

Drakos, N. 2019. “Digital Workplace Program Primer for 2019,” Gartner, Inc. (ed.).

Drechsler, A., and Hevner, A. R. 2018. “Utilizing, producing, and contributing design knowledge in DSR projects,” in *International Conference on Design Science Research in Information Systems and Technology*, Springer, pp. 82-97.

Dunn, K. J., and McCray, G. 2020. “The Place of the Bifactor Model in Confirmatory Factor Analysis Investigations Into Construct Dimensionality in Language Testing,” *Frontiers in Psychology* (11), p. 1357 (doi: 10.3389/fpsyg.2020.01357).

Earnshaw, J., and Cooper, C. L. 2000. *Stress and Employer Liability*: *Developing Practice*, London: Chartered Institute of Personnel and Development.

Eisenberg, M. B., Lowe, C. A., and Spitzer, K. L. 2006. “Information literacy,” *Public Library*.

Elgharib, M., Hefeeda, M., Durand, F., and Freeman, W. T. 2015. “Video Magnification in Presence of Large Motions,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 4119-4127.

Elliot, A. J., and Niesta, D. 2009. “Goals in the Context of the Hierarchical Model of Approach–Avoidance Motivation,” in *The Psychology of Goals*, G. B. Moskowitz and H. Grant (eds.), New York, New York, The United States of America: Guilford Press, pp. 56-76.

Erschens, R., Loda, T., Herrmann-Werner, A., Keifenheim, K. E., Stuber, F., Nikendei, C., Zipfel, S., and Junne, F. 2018. “Behaviour-based functional and dysfunctional strategies of medical students to cope with burnout," *Medical Education Online* (23:1), p. 1535738 (doi: 10.1080/10872981.2018.1535738).

European Commission 2015. *Privacy Code of Conduct on mobile health apps - Shaping Europe's digital future - European Commission*. https://ec.europa.eu/digital-single-market/en/privacy-code-conduct-mobile-health-apps. Accessed 18 December 2020.

Federal Statistical Office of Germany 2018a. *Erwerbstätige und Arbeitnehmer nach Wirtschaftsbereichen (Inlandskonzept) 1 000 Personen*. https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Erwerbstaetigkeit/Tabellen/arbeitnehmer-wirtschaftsbereiche.html. Accessed 18 December 2020.

Federal Statistical Office of Germany 2018b. *Erwerbstätige und Erwerbstätigenquote nach Geschlecht und Alter 2008 und 2018*: *Ergebnis des Mikrozensus*. https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Erwerbstaetigkeit/Tabellen/erwerbstaetige-erwerbstaetigenquote.html. Accessed 18 December 2020.

Fehm, L. B. 1999. "Unerwünschte Gedanken bei Angststörungen: Diagnostik und experimentelle Befunde," (Doctoral dissertation, Technische Universität Dresden).

Fehrenbacher, D. 2017. "Affect Infusion and Detection through Faces in Computer-mediated Knowledge-sharing Decisions," *Journal of the Association for Information Systems* (18:10), pp. 703-726 (doi: 10.17705/1jais.00470).

Ferdous, R., Osmani, V., Beltran Marquez, J., and Mayora, O. 2015. "Investigating correlation between verbal interactions and perceived stress," *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference* (2015), pp. 1612-1615 (doi: 10.1109/EMBC.2015.7318683).

Fernandez, R., and Picard, R. W. 2003. "Modeling drivers' speech under stress," *Speech communication* (40:1-2), pp. 145-159 (doi: 10.1016/S0167-6393(02)00080-8).

Ferreira, P., Sanches, P., Höök, K., and Jaensson, T. 2009. "License to chill!," in *Proceedings of the Nordic Conference on Human-computer Interaction*, Lund, Sweden. Oct 20-22, 2008, p. 123.

Festinger, L. 1957. *A theory of cognitive dissonance*, Stanford university press.

Fischer, T., Pehböck, A., and Riedl, R. 2019. "Is the Technostress Creators Inventory Still an Up-To-Date Measurement Instrument? Results of a Large-Scale Interview Study," in *14th International Conference on Wirtschaftsinformatik*, Siegen.

Fischer, T., and Riedl, R. 2015. "Theorizing Technostress in Organizations: A Cybernetic Approach," in *12th International Conference on Wirtschaftsinformatik,* Osnabrück, pp. 1453-1467.

Fischer, T., and Riedl, R. 2019. *Lifelogging for Organizational Stress Measurement,* Cham: Springer International Publishing.

Fischer, T., and Riedl, R. 2020. "On the stress potential of an organisational climate of innovation: a survey study in Germany," *Behaviour & Information Technology* (67:1), pp. 1-22 (doi: 10.1080/0144929X.2020.1836258).

Fitzgerald, M., Kruschwitz, N., Bonnet, D., and Welch, M. 2013. "Embracing Digital Technology: A New Strategic Imperative," *MIT Sloan Management Review* (55:2), pp. 1-12.

Florkowski, G. W. 2019. "HR technologies and HR-staff technostress: an unavoidable or combatable effect?" *Employee Relations* (41:5), pp. 1120-1144 (doi: 10.1108/ER-08-2018-0214).

Foley, P., and Kirschbaum, C. 2010. "Human hypothalamus-pituitary-adrenal axis responses to acute psychosocial stress in laboratory settings," *Neuroscience & Biobehavioral Reviews* (35:1), pp. 91-96 (doi: 10.1016/j.neubiorev.2010.01.010).

Folkman, S., and Lazarus, R. S. 1984. *Stress, appraisal, and coping,* New York: Springer Publishing Company.

Folkman, S., Lazarus, R. S., Dunkel-Schetter, C., DeLongis, A., and Gruen, R. J. 1986. "Dynamics of a stressful encounter: Cognitive appraisal, coping, and encounter outcomes," *Journal of personality and social psychology* (50:5), pp. 992-1003 (doi: 10.1037/0022-3514.50.5.992).

Forero, C. G., Maydeu-Olivares, A., and Gallardo-Pujol, D. 2009. "Factor Analysis with Ordinal Indicators: A Monte Carlo Study Comparing DWLS and ULS Estimation," *Structural Equation Modeling: A Multidisciplinary Journal* (16:4), pp. 625-641 (doi: 10.1080/10705510903203573).

Forman, C., King, J. L., and Lyytinen, K. 2014. "Special Section Introduction—Information, Technology, and the Changing Nature of Work," *Information Systems Research* (25:4), pp. 789-795 (doi: 10.1287/isre.2014.0551).

Fornell, C., and Larcker, D. F. 1981. "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," *Journal of Marketing Research* (18:1), p. 39 (doi: 10.2307/3151312).

Frese, M. 1986. “Coping as a Moderator and Mediator between Stress at Work and Psychosomatic Complaints,” in *Dynamics of Stress*, M. H. Appley and R. Trumbull (eds.), Boston, MA: Springer US, pp. 183-206.

Friemel, C., Morana, S., Pfeiffer, J., and Maedche, A. 2018. “On the Role of Users’ Cognitive-Affective States for User Assistance Invocation,” in *Information Systems and Neuroscience*: *Lecture Notes in Information Systems and Organisation*, F. Davis, R. Riedl, J. Vom Brocke, P.-M. Léger and A. Randolph (eds.), Cham: Springer, pp. 37-46.

Fritz, C. O., Morris, P. E., and Richler, J. J. 2012. “Effect size estimates: current use, calculations, and interpretation,” *Journal of Experimental Psychology General* (141:1), pp. 2-18 (doi: 10.1037/a0024338).

Fuller, M. A., Hardin, A. M., and Davison, R. M. 2006. “Efficacy in Technology-Mediated Distributed Teams,” *Journal of Management Information Systems* (23:3), pp. 209-235 (doi: 10.2753/MIS0742-1222230308).

Gaggioli, A., Pioggia, G., Tartarisco, G., Baldus, G., Corda, D., Cipresso, P., and Riva, G. 2013. “A mobile data collection platform for mental health research,” *Personal and ubiquitous computing* (17:2), pp. 241-251 (doi: 10.1007/s00779-011-0465-2).

Gajendran, R. S., and Harrison, D. A. 2007. “The good, the bad, and the unknown about telecommuting: meta-analysis of psychological mediators and individual consequences,” *The Journal of applied psychology* (92:6), pp. 1524-1541 (doi: 10.1037/0021-9010.92.6.1524).

Galluch, P., Grover, V., and Thatcher, J. 2015. “Interrupting the Workplace: Examining Stressors in an Information Technology Context,” *Journal of the Association for Information Systems* (16:1), pp. 1-47 (doi: 10.17705/1jais.00387).

Gao, H., Yuce, A., and Thiran, J.-P. 2014. “Detecting emotional stress from facial expressions for driving safety,” in *IEEE International Conference on Image Processing (ICIP), 2014*: *27 - 30 Oct. 2014, Paris, France,* Paris, France. 10/27/2014 - 10/30/2014, Piscataway, NJ: IEEE, pp. 5961-5965.

Gao et al. 2007. “Digital Filtering of Pupil Diameter Variations for the Detection of Stress in Computer Users,”

Garcia-Ceja, E., Osmani, V., and Mayora, O. 2016. “Automatic Stress Detection in Working Environments From Smartphones' Accelerometer Data: A First Step,” *Journal of Biomedical and Health Informatics* (20:4), pp. 1053-1060 (doi: 10.1109/JBHI.2015.2446195).

Gartner 2020. *Gartner IT Glossary > Digital Workplace*. http://www.gartner.com/it-glossary/digital-workplace. Accessed 18 December 2020.

Gaudioso, F., Turel, O., and Galimberti, C. 2016. "Explaining work exhaustion from a coping theory perspective: Roles of techno-stressors and technology-specific coping strategies," *Studies in Health Technology and Informatics* (219), pp. 14-20 (doi: 10.3233/978-1-61499-595-1-14).

Gaudioso, F., Turel, O., and Galimberti, C. 2017. "The mediating roles of strain facets and coping strategies in translating techno-stressors into adverse job outcomes," *Computers in Human Behavior* (69), pp. 189-196 (doi: 10.1016/j.chb.2016.12.041).

Gefen, D., Straub, D., and Boudreau, M.-C. 2000. "Structural Equation Modeling and Regression: Guidelines for Research Practice," *Communications of the Association for Information Systems* (4) (doi: 10.17705/1CAIS.00407).

Geiser, C. 2011. *Datenanalyse mit Mplus*: *Eine anwendungsorientierte Einführung*, Wiesbaden: VS Verlag für Sozialwissenschaften.

Gentry, W. D. (ed.) 1984. *The Handbook of Behavioral Medicine*, New York: Guilford.

Gilson, L. L., Maynard, M. T., Jones Young, N. C., Vartiainen, M., and Hakonen, M. 2015. "Virtual Teams Research," *Journal of management* (41:5), pp. 1313-1337 (doi: 10.1177/0149206314559946).

Gimpel, H. 2019. "Gesund digital arbeiten?!: Eine Studie zu digitalem Stress in Deutschland," Augsburg: Fraunhofer-Gesellschaft.

Gimpel, H., Hosseini, S., Huber, R., Probst, L., Röglinger, M., and Faisst, U. 2018a. "Structuring Digital Transformation: A Framework of Action Fields and its Application at ZEISS," *Journal of Information Technology Theory and Application* (19:1), pp. 31-54.

Gimpel, H., Lanzl, J., Manner-Romberg, T., and Nüske, N. 2018b. "Digitaler Stress in Deutschland: Eine Befragung von Erwerbstätigen zu Belastung und Beanspruchung durch Arbeit mit digitalen Technologien," Hans Böckler Stiftung (ed.).

Gimpel, H., Lanzl, J., Urbach, N., Regal, C., Becker, J., Kühlmann, T. M., and Certa, M. 2020a. "Extending the Concept of Technostress: The Hierarchical Structure of Digital Stress," *Working Paper*.

Gimpel, H., Nißen, M., and Görlitz, R. A. 2013. "Quantifying the Quantified Self: A Study on the Motivations of Patients to Track Their Own Health," in *Thirty Fourth International Conference on Information Systems 2013*.

Gimpel, H., Nüske, N., and Regal, C. 2020b. "How to Conquer One's Weaker Self: Do Autonomy Affordance Increase Goal Performance and Well-being?" in *53nd Hawaii International Conference on System Sciences*.

Gimpel, H., Regal, C., and Schmidt, M. 2015. "myStress: Unobtrusive Smartphone-Based Stress Detection," in *Proceedings of the European Conference on Information System,* Münster, Germany.

Gimpel, H., Regal, C., and Schmidt, M. 2019a. "Design Knowledge on Mobile Stress Assessment," in *40th International Conference on Information Systems (ICIS)*.

Gimpel, H., Regal, C., and Schmidt, M. 2019b. "Life-Integrated Stress Assessment," in *Proceedings of the 27th European Conference on Information Systems (ECIS),* Stockholm & Uppsala. June 8-14, Sweden, https://aisel.aisnet.org/ecis2019_rp/132.

Gimpel, H., and Schmied, F. 2019. "Risks and Side Effects of Digitalization : A Multi-Level Taxonomy of the Adverse Effects of Using Digital Technologies and Media," in *Proceedings of the 27th European Conference on Information Systems*, Stockholm, Uppsala.

Gjoreski, M., Gjoreski, H., Lutrek, M., and Gams, M. 2015. "Automatic Detection of Perceived Stress in Campus Students Using Smartphones," Proceedings of the International Conference on Intelligent Environments, pp. 132-135.

Glaser, B. G., and Strauss, A. 2017. *Discovery of Grounded Theory: Strategies for Qualitative Research*, Routledge.

Glenn, T., and Monteith, S. 2014. "New measures of mental state and behavior based on data collected from sensors, smartphones, and the Internet," *Computers in Human Behavior* (16:12), p. 523 (doi: 10.1007/s11920-014-0523-3).

Goad, T. W. 2002. *Information literacy and workplace performance*, Greenwood Publishing Group.

Goes, P. B. 2013. "Editor's comments: commonalities across IS silos and intradisciplinary information systems research," *MIS Quarterly* (37:2), pp. iii-vii.

Goh, J., Pfeffer, J., and Zenios, S. A. 2016. "The Relationship Between Workplace Stressors and Mortality and Health Costs in the United States," *Management Science* (62:2), pp. 608-628 (doi: 10.1287/mnsc.2014.2115).

Golden, T. D. 2012. "Altering the Effects of Work and Family Conflict on Exhaustion: Telework During Traditional and Nontraditional Work Hours," *Journal of Business and Psychology* (27:3), pp. 255-269 (doi: 10.1007/s10869-011-9247-0).

Goodell, J. 1994. “Steve Jobs: The Rolling Stone Interview,” *Rolling Stone*.

Greene, S., Thapliyal, H., and Caban-Holt, A. 2016. “A Survey of Affective Computing for Stress Detection: Evaluating technologies in stress detection for better health,” *IEEE Consumer Electronics Magazine* (5:4), pp. 44-56 (doi: 10.1109/MCE.2016.2590178).

Gregor, S. 2006. “The Nature of Theory in Information Systems,” *MIS Quarterly* (30:3), pp. 611-642.

Gregor, S., and Hevner, A. R. 2013. “Positioning and Presenting Design Science Research for Maximum Impact,” *MIS Quarterly* (37:2), pp. 337-355 (doi: 10.25300/MISQ/2013/37.2.01).

Griffith, T. L., Fuller, M. A., and Northcraft, G. B. 1998. “Facilitator Influence in Group Support Systems: Intended and Unintended Effects,” *Information Systems Research* (9:1), pp. 20-36 (doi: 10.1287/isre.9.1.20).

Haas, M. R., Criscuolo, P., and George, G. 2015. “Which Problems to Solve? Online Knowledge Sharing and Attention Allocation in Organizations,” *Academy of Management Journal* (58:3), pp. 680-711 (doi: 10.5465/amj.2013.0263).

Habib ur Rehman, M., Liew, C. S., Wah, T. Y., Shuja, J., and Daghighi, B. 2015. “Mining personal data using smartphones and wearable devices: a survey,” *Sensors* (15:2), pp. 4430-4469 (doi: 10.3390/s150204430).

Hall, M. 2015. *Detecting Well-being in Digital Communities: An Interdisciplinary Engineering Approach for its Indicators*. Doctoral Thesis, Karlsruhe.

Hammen, C. 2005. “Stress and depression,” *Annual review of clinical psychology* (1), pp. 293-319 (doi: 10.1146/annurev.clinpsy.1.102803.143938).

Harker Martin, B., and MacDonnell, R. 2012. “Is telework effective for organizations?” *Management Research Review* (35:7), pp. 602-616 (doi: 10.1108/01409171211238820).

Harkin, B., Webb, T. L., Chang, B. P. I., Prestwich, A., Conner, M., Kellar, I., Benn, Y., and Sheeran, P. 2016. “Does monitoring goal progress promote goal attainment? A meta-analysis of the experimental evidence,” *Psychological Bulletin* (142:2), pp. 198-229 (doi: 10.1037/bul0000025).

Harman, H. H. 1967. *Modern factor analysis*, Chicago, IL: University of Chicago Press.

Hastie, T., Tibshirani, R., Friedman, J., and Franklin, J. 2005. “The elements of statistical learning: data mining, inference and prediction,” *The Mathematical Intelligencer* (27:2), pp. 83-85.

Hatcliff, J., King, A., Lee, I., Macdonald, A., Fernando, A., Robkin, M., Vasserman, E., Weininger, S., and Goldman, J. M. 2012. "Rationale and architecture principles for medical application platforms," in *IEEE/ACM Third International Conference on Cyber-Physical Systems*, IEEE, pp. 3-12.

Hauk, N., Göritz, A. S., and Krumm, S. 2019. "The mediating role of coping behavior on the age-technostress relationship: A longitudinal multilevel mediation model," *PloS one* (14:3), e0213349 (doi: 10.1371/journal.pone.0213349).

Haushofer, J., and Fehr, E. 2014. "On the psychology of poverty," *Science* (344:6186), pp. 862-867 (doi: 10.1126/science.1232491).

Hayes, A. F. 2013. *Introduction to mediation, moderation, and conditional process analysis*: *A regression-based approach*, New York, NY: The Guilford Press.

Hefner, D., and Vorderer, P. 2016. "Permanent connectedness and multitasking," in *The Routledge Handbook of Media Use and Well-Being: International Perspectives on Theory and Research on Positive Media*, L. Reinecke and M. B. Oliver (eds.), New York: Routledge, pp. 237-249.

Heidt, T., Sager, H. B., Courties, G., Dutta, P., Iwamoto, Y., Zaltsman, A., zur Muhlen, C. von, Bode, C., Fricchione, G. L., Denninger, J., Lin, C. P., Vinegoni, C., Libby, P., Swirski, F. K., Weissleder, R., and Nahrendorf, M. 2014. "Chronic variable stress activates hematopoietic stem cells," *Nature Medicine* (20:7), pp. 754-758 (doi: 10.1038/nm.3589).

Henseler, J., Ringle, C. M., and Sarstedt, M. 2015. "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science* (43:1), pp. 115-135 (doi: 10.1007/s11747-014-0403-8).

Hess, T., Legner, C., Esswein, W., Maaß, W., Matt, C., Österle, H., Schlieter, H., Richter, P., and Zarnekow, R. 2014. "Digital Life as a Topic of Business and Information Systems Engineering?" *Business & Information Systems Engineering* (6:4), pp. 247-253 (doi: 10.1007/s12599-014-0332-6).

Hevner, A., Vom Brocke, J., and Maedche, A. 2019. "Roles of Digital Innovation in Design Science Research," *Business & Information Systems Engineering: Vol. 61, No. 1* (61:1), pp. 3-8 (doi: 10.1007/s12599-018-0571-z).

Hevner, A. R., March, S. T., Park, J., and Ram, S. 2004. "Design Science in Information Systems Research," *MIS Quarterly* (28:1), pp. 75-105.

Hinkin, T. R. 1998. “A Brief Tutorial on the Development of Measures for Use in Survey Questionnaires,” *Organizational research methods* (1:1), pp. 104-121 (doi: 10.1177/109442819800100106).

Hirschi, T., and Selvin, H. C. 2017. *Delinquency Research: An Appraisal of Analytic Methods*, Routledge.

Hobfoll, S. E. 1989. “Conservation of resources: A new attempt at conceptualizing stress,” *American Psychologist* (44:3), pp. 513-524 (doi: 10.1037/0003-066X.44.3.513).

Hobfoll, S. E., and Wells, J. D. 1998. “Conservation of resources, stress, and aging,” in *Handbook of aging and mental health*, Springer, pp. 121-134.

Hoffmann, R. 2018. *Hohe emotionale Belastungen bei der Arbeit mit Menschen*. https://www.dgb.de/presse/++co++d993c67a-ee32-11e8-ba59-52540088cada. Accessed 18 December 2020.

Hofmans, J., Debusscher, J., Dóci, E., Spanouli, A., and Fruyt, F. de 2015. “The curvilinear relationship between work pressure and momentary task performance: the role of state and trait core self-evaluations,” *Frontiers in Psychology* (6), p. 1680 (doi: 10.3389/fpsyg.2015.01680).

Holmes, T. H., and Rahe, R. H. 1967. “The social readjustment rating scale,” *Journal of Psychosomatic Research* (11:2), pp. 213-218 (doi: 10.1016/0022-3999(67)90010-4).

Hong, W., Chan, F. K. Y., Thong, J. Y. L., Chasalow, L. C., and Dhillon, G. 2014. “A Framework and Guidelines for Context-Specific Theorizing in Information Systems Research,” *Information Systems Research* (25:1), pp. 111-136 (doi: 10.1287/isre.2013.0501).

Hovsepian, K., Al'Absi, M., Ertin, E., Kamarck, T., Nakajima, M., and Kumar, S. 2015. “cStress: Towards a Gold Standard for Continuous Stress Assessment in the Mobile Environment,” in *Proceedings of the International Conference on Ubiquitous Computing . UbiComp (Conference)*, pp. 493-504.

Hu, L., and Bentler, P. M. 1999. “Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives,” *Structural Equation Modeling: A Multidisciplinary Journal* (6:1), pp. 1-55 (doi: 10.1080/10705519909540118).

Huh, J., Shin, H., Leventhal, A. M., Spruijt-Metz, D., Abramova, Z., Cerrada, C., Hedeker, D., and Dunton, G. 2014. “Momentary negative moods and being with friends precede cigarette use among Korean American emerging adults,” *Nicotine & tobacco research :*

official journal of the Society for Research on Nicotine and Tobacco (16:9), pp. 1248-1254 (doi: 10.1093/ntr/ntu063).

Hume, D. 2003. *A treatise of human nature,* Courier Corporation.

Hung, W.-H., Chen, K., and Lin, C.-P. 2015. "Does the proactive personality mitigate the adverse effect of technostress on productivity in the mobile environment?" *Telematics and Informatics* (32:1), pp. 143-157 (doi: 10.1016/j.tele.2014.06.002).

Huppert, F. A., and So, T. T. C. 2009. "What percentage of people in Europe are flourishing and what characterises them?: Prepared for the OECD/ISQOLS meeting "Measuring subjective well-being: an opportunity for NSOs?" in Florence - July 23/24, 2009," University of Cambridge, The Well-being Institute.

Intille, S. S., Rondoni, J., Kukla, C., Ancona, I., and Bao, L. 2003. "A context-aware experience sampling tool," in *CHI '03 Extended Abstracts on Human Factors in Computing Systems,* New York, NY, USA: ACM, p. 972.

Janssen, O. 2001. "FAIRNESS PERCEPTIONS AS A MODERATOR IN THE CURVILINEAR RELATIONSHIPS BETWEEN JOB DEMANDS, AND JOB PERFORMANCE AND JOB SATISFACTION," *Academy of Management Journal* (44:5), pp. 1039-1050 (doi: 10.2307/3069447).

Jennrich, R. I., and Bentler, P. M. 2011. "Exploratory Bi-factor Analysis," *Psychometrika* (76:4), pp. 537-549 (doi: 10.1007/s11336-011-9218-4).

Jewell, L. N. 1998. *Contemporary Industrial/Organizational Psychology*, Belmont, CA: Wadsworth Publishing.

Jimenez, P., and Bregenzer, A. 2018. "Integration of eHealth Tools in the Process of Workplace Health Promotion: Proposal for Design and Implementation," *Journal of medical Internet research* (20:2), e65 (doi: 10.2196/jmir.8769).

Jones, D., and Gregor, S. 2007. "The Anatomy of a Design Theory," *Journal of the Association for Information Systems* (8:5), pp. 312-335 (doi: 10.17705/1jais.00129).

Jöreskog, K. G. 1970. "A GENERAL METHOD FOR ESTIMATING A LINEAR STRUCTURAL EQUATION SYSTEM*," *ETS Research Bulletin Series* (1970:2), i-41 (doi: 10.1002/j.2333-8504.1970.tb00783.x).

Jöreskog, K. G., and Yang, F. 2013. "Nonlinear structural equation models: The Kenny-Judd model with interaction effects," in *Advanced Structural Equation Modeling*, G. A. Marcoulides (ed.), Psychology Press, pp. 57-88.

Jorgensen, T. D., Pornprasertmanit, S., Schoemann, A. M., and Rossel, Y. 2019. *SemTools: Useful Tools for Structural Equation Modeling*.

Kahler, C. W., Ramsey, S. E., Read, J. P., and Brown, R. A. 2002. “Substance-induced and independent major depressive disorder in treatment-seeking alcoholics: associations with dysfunctional attitudes and coping,” *Journal of Studies on Alcohol* (63:3), pp. 363-371 (doi: 10.15288/jsa.2002.63.363).

Kees, J., Berry, C., Burton, S., and Sheehan, K. 2017. “An Analysis of Data Quality: Professional Panels, Student Subject Pools, and Amazon's Mechanical Turk,” *Journal of Advertising* (46:1), pp. 141-155 (doi: 10.1080/00913367.2016.1269304).

Kenny, D. A., and Judd, C. M. 1984. “Estimating the nonlinear and interactive effects of latent variables,” *Psychological Bulletin* (96:1), pp. 201-210 (doi: 10.1037/0033-2909.96.1.201).

Khaoula, S., Khalid, C., and Omar, T. 2020. “The Impact of Stress Due to Digital Communication on Productivity: The Exploratory Study,” *International Journal of Business and Administrative Studies* (6:4) (doi: 10.20469/ijbas.6.10003-4).

Kirmeyer, S. L. 1988. “Coping with competing demands: interruption and the type A pattern,” *The Journal of applied psychology* (73:4), pp. 621-629 (doi: 10.1037/0021-9010.73.4.621).

Klotz, U. 1997. “Informationsarbeit und das Ende des Taylorismus,” in *Schöne neue Arbeit: Die Zukunft der Arbeit vor dem Hintergrund neuer Informationstechnologien*, J. Krämer, J. Richter, J. Wandel and G. Zinsmeister (eds.), Mössingen-Talheim: Talheimer, pp. 113-134.

Klug, H. J. P., and Maier, G. W. 2015. “Linking Goal Progress and Subjective Well-Being: A Meta-analysis: A Meta-analysis,” *Journal of Happiness Studies* (16:1), pp. 37-65 (doi: 10.1007/s10902-013-9493-0).

Knoll, N., Rieckmann, N., and Schwarzer, R. 2005. “Coping as a mediator between personality and stress outcomes: a longitudinal study with cataract surgery patients,” *European Journal of personality* (19:3), pp. 229-247 (doi: 10.1002/per.546).

Kocielnik, R., Sidorova, N., Maggi, F. M., Ouwerkerk, M., and Westerink, J. H. D. M. 2013. “Smart technologies for long-term stress monitoring at work,” in *Proceedings of the 26th International Symposium on Computer-Based Medical Systems,* Porto, Portugal. Jun 20-22, 2013, IEEE, pp. 53-58.

Koestner, R., Lekes, N., Powers, T. A., and Chicoine, E. 2002. "Attaining personal goals: Self-concordance plus implementation intentions equals success: Self-concordance plus implementation intentions equals success," *Journal of personality and social psychology* (83:1), pp. 231-244 (doi: 10.1037//0022-3514.83.1.231).

Koestner, R., Otis, N., Powers, T. A., Pelletier, L., and Gagnon, H. 2008. "Autonomous motivation, controlled motivation, and goal progress," *Journal of personality* (76:5), pp. 1201-1230 (doi: 10.1111/j.1467-6494.2008.00519.x).

Köffer, S. 2015. "Designing the Digital Workplace of the Future - What Scholars Recommend to Practitioners," in *Proceedings of the 36th International Conference on Information Systems (ICIS)*, Fort Worth, Texas. USA.

Köffer, S., Anlauf, L., Ortbach, K., and Niehaves, B. 2015. "The Intensified Blurring of Boundaries Between Work and Private Life through IT Consumerisation," in *Proceedings of the European Conference on Information System*, Münster, Germany.

Kortte, K. B., Wegener, S. T., and Chwalisz, K. 2003. "Anosognosia and denial: Their relationship to coping and depression in acquired brain injury," *Rehabilitation Psychology* (48:3), pp. 131-136 (doi: 10.1037/0090-5550.48.3.131).

Krueger, A. B., and Schkade, D. A. 2008. "The Reliability of Subjective Well-Being Measures," *Journal of public economics* (92:8-9), pp. 1833-1845 (doi: 10.1016/j.jpubeco.2007.12.015).

La Torre, G., Esposito, A., Sciarra, I., and Chiappetta, M. 2019. "Definition, symptoms and risk of techno-stress: a systematic review," *International archives of occupational and environmental health* (92:1), pp. 13-35 (doi: 10.1007/s00420-018-1352-1).

La Torre, G., Leonardis, V. de, and Chiappetta, M. 2020. "Technostress: how does it affect the productivity and life of an individual? Results of an observational study," *Public Health* (189), pp. 60-65 (doi: 10.1016/j.puhe.2020.09.013).

Lane, N., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., and Campbell, A. 2010. "A survey of mobile phone sensing," *Communications Magazine, IEEE* (48:9), pp. 140-150 (doi: 10.1109/MCOM.2010.5560598).

Lane, N. D., Mohammod, M., Lin, M., Yang, X., Lu, H., Ali, S., Doryab, A., Berke, E., Choudhury, T., and Campbell, A. T. 2011. "BeWell: A Smartphone Application to Monitor, Model and Promote Wellbeing," in *Proceedings of the International ICST Conference on Pervasive Computing Technologies for Healthcare*, Dublin, Ireland. May 23-26, 2011, pp. 23-26.

Lawanont, W., and Inoue, M. 2018. "An unsupervised learning method for perceived stress level recognition based on office working behavior," in *2018 International Conference on Electronics, Information, and Communication (ICEIC)*, Honolulu, HI. 2018, IEEE, pp. 1-4.

Lazarsfeld, P. F. 1955. "Interpretation of statistical relations as a research operation," *The language of social research: A reader in the methodology of social research*, pp. 115-125.

Lazarus, R. S. 1993. "Coping theory and research: past, present, and future," *Fifty years of the research and theory of RS Lazarus: An analysis of historical and perennial issues* (55:3), pp. 234-247 (doi: 10.1097/00006842-199305000-00002).

Lazarus, R. S., and Folkman, S. 1984. *Stress, Appraisal, and Coping*, New York: Springer Pub. Co.

Lazarus, R. S., and Folkman, S. 1987. "Transactional theory and research on emotions and coping," *European Journal of personality* (1:3), pp. 141-169 (doi: 10.1002/per.2410010304).

Lee, A. S., Thomas, M., and Baskerville, R. L. 2015. "Going back to basics in design science: from the information technology artifact to the information systems artifact," *Information Systems Journal* (25:1), pp. 5-21 (doi: 10.1111/isj.12054).

Lee, B.-G., and Chung, W.-Y. 2017. "Wearable Glove-Type Driver Stress Detection Using a Motion Sensor," *IEEE Transactions on Intelligent Transportation Systems* (18:7), pp. 1835-1844 (doi: 10.1109/TITS.2016.2617881).

Lee, D. S., Chong, T. W., and Lee, B. G. 2016. "Stress Events Detection of Driver by Wearable Glove System," *IEEE Sensors Journal*, p. 1 (doi: 10.1109/JSEN.2016.2625323).

Lee, H., Choi, Y. S., Lee, S., and Park, I. P. 2012. "Towards unobtrusive emotion recognition for affective social communication," in *Proceedings of the IEEE Consumer Communications and Networking Conference*, Las Vegas, NV. Jan 14-17, 2012, pp. 260-264.

Lee, H., Park, K., Lee, B., Choi, J., and Elmasri, R. 2008. "Issues in data fusion for healthcare monitoring," in *Proceedings of the 1st international conference on PErvasive Technologies Related to Assistive Environments*, pp. 1-8.

Lee, Y.-K., Chang, C.-T., Lin, Y., and Cheng, Z.-H. 2014. "The dark side of smartphone usage: Psychological traits, compulsive behavior and technostress," *Computers in Human Behavior* (31:1), pp. 373-383 (doi: 10.1016/j.chb.2013.10.047).

Lefter, I., Burghouts, G. J., and Rothkrantz, L. J. 2016. "Recognizing Stress Using Semantics and Modulation of Speech and Gestures," *IEEE Transactions on Affective Computing* (7:2), pp. 162-175 (doi: 10.1109/TAFFC.2015.2451622).

Legner, C., Eymann, T., Hess, T., Matt, C., Böhmann, T., Drews, P., Mädche, A., Urbach, N., and Ahlemann, F. 2017. "Digitalization: Opportunity and Challenge for the Business and Information Systems Engineering Community," *Business & Information Systems Engineering* (59:4), pp. 301-308 (doi: 10.1007/s12599-017-0484-2).

Lei, P.-W., and Wu, Q. 2007. "Introduction to Structural Equation Modeling: Issues and Practical Considerations," *Educational Measurement: issues and practice* (26:3), pp. 33-43 (doi: 10.1111/j.1745-3992.2007.00099.x).

Leidner, D. E. 2020. "What's in a Contribution?" *Journal of the Association for Information Systems*, pp. 238-245 (doi: 10.17705/1jais.00598).

Leung, K., Huang, K.-L., Su, C.-H., and Lu, L. 2011. "Curvilinear relationships between role stress and innovative performance: Moderating effects of perceived support for innovation," *Journal of Occupational and Organizational Psychology* (84:4), pp. 741-758 (doi: 10.1348/096317910X520421).

Lewin, J. E., and Sager, J. K. 2009. "An investigation of the influence of coping resources in salespersons' emotional exhaustion," *Industrial Marketing Management* (38:7), pp. 798-805 (doi: 10.1016/j.indmarman.2008.02.013).

Liao, W., Zhang, W., Zhu, Z., and Ji, Q. 2005. "A Real-Time Human Stress Monitoring System Using Dynamic Bayesian Network," in *CVPR 2005*: *Proceedings : 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, C. Schmid, C. Tomasi and S. Soatto (eds.), San Diego, CA, USA. 20-26 June 2005, Los Alamitos, Calif: IEEE Computer Society, p. 70.

LiKamWa, R., Liu, Y., Lane, N. D., and Zhong, L. 2013. "MoodScope," in *Proceedings of the International Conference on Mobile Systems, Applications, and Services,* Taipei, Taiwan. Jun 25-28, 2013, p. 389.

Lin, G.-C., Wen, Z., Marsh, H., and Lin, H.-S. 2010a. "Structural Equation Models of Latent Interactions: Clarification of Orthogonalizing and Double-Mean-Centering Strategies," *Structural Equation Modeling: A Multidisciplinary Journal* (17:3), pp. 374-391 (doi: 10.1080/10705511.2010.488999).

Lin, H.-S., Probst, J. C., and Hsu, Y.-C. 2010b. "Depression among female psychiatric nurses in southern Taiwan: main and moderating effects of job stress, coping behaviour and social support," *Journal of clinical nursing* (19:15-16), pp. 2342-2354 (doi: 10.1111/j.1365-2702.2010.03216.x).

Lindell, M. K., and Whitney, D. J. 2001. "Accounting for common method variance in cross-sectional research designs," *The Journal of applied psychology* (86:1), pp. 114-121 (doi: 10.1037/0021-9010.86.1.114).

Little, T. D. 1997. "Mean and Covariance Structures (MACS) Analyses of Cross-Cultural Data: Practical and Theoretical Issues," *Multivariate behavioral research* (32:1), pp. 53-76 (doi: 10.1207/s15327906mbr3201_3).

Little, T. D., and Kline, R. B. (eds.) 2016. *Principles and practice of structural equation modeling*, New York, London: The Guilford Press.

Locke, E. A., and Latham, G. P. 2002. "Building a practically useful theory of goal setting and task motivation: A 35-year odyssey," *American Psychologist* (57:9), pp. 705-717 (doi: 10.1037/0003-066X.57.9.705).

Lu, H., Frauendorfer, D., Rabbi, M., Mast, M. S., Chittaranjan, G. T., Campbell, A. T., Gatica-Perez, D., and Choudhury, T. 2012. "StressSense," in *Proceedings of the ACM Conference on Ubiquitous Computing*, p. 351.

Lupton, D. 2014a. "Self-tracking cultures: towards a sociology of personal informatics," in *Proceedings of the 26th Australian Computer-Human Interaction Conference on Designing Futures: the Future of Design,* Sydney, New South Wales, Australia. 2 - 5 December, pp. 77-86.

Lupton, D. 2014b. "Self-tracking Modes: Reflexive Self-Monitoring and Data Practices: Paper for the 'Imminent Citizenships: Personhood and Identity Politics in the Informatic Age' workshop, 27 August 2014, ANU, Canberra," University of Canberra, Faculty of Arts & Design, News & Media Research Centre, Canberra, Australia.

MacKenzie, and Podsakoff 2011. "Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques," *MIS Quarterly* (35:2), p. 293 (doi: 10.2307/23044045).

MacKinnon, D. P., Krull, J. L., and Lockwood, C. M. 2000. "Equivalence of the mediation, confounding and suppression effect," *Prevention Science* (1:4), pp. 173-181 (doi: 10.1023/a:1026595011371).

Maedche, A., Morana, S., Schacht, S., Werth, D., and Krumeich, J. 2016. "Advanced User Assistance Systems," *Business & Information Systems Engineering* (58:5), pp. 367-370 (doi: 10.1007/s12599-016-0444-2).

Mahapatra, M., and Pati, S. P. 2018a. "Technostress Creators and Burnout," in *Proceedings of the 2018 ACM SIGMIS Conference on Computers and People Research (SIGMIS-CPR'18),* Buffalo-Niagara Falls, NY, USA, pp. 70-77.

Mahapatra, M., and Pati, S. P. 2018b. "Technostress creators and burnout: A Job Demands-Resources Perspective," in *Proceedings of the 2018 ACM SIGMIS Conference on Computers and People Research (SIGMIS-CPR'18),* Buffalo-Niagara Falls, NY, USA, pp. 70-77.

Mahwah, N. (ed.) 2010. *Psychophysiology*: *Human Behavior & Physiological Response*, Lawrence Erlbaum Associates Inc Mahwah, NJ.

Maier, C., Laumer, S., and Weinert, C. 2015. "Enterprise Resource Planning Systems Induced Stress: A Comparative Empirical Analysis with Young and Elderly SAP Users," in *Proceedings of the 12th International Conference on Wirtschaftsinformatik (WI15)*, Osnabrück, Germany.

Maier, C., Laumer, S., Wirth, J., and Weitzel, T. 2019. "Technostress and the hierarchical levels of personality: a two-wave study with multiple data samples," *European Journal of Information Systems* (28:5), pp. 496-522 (doi: 10.1080/0960085X.2019.1614739).

Majchrzak, A., Markus, M. L., and Wareham, J. 2016. "Designing for Digital Transformation: Lessons for Information Systems Research from the Study of ICT and Societal Challenges," *MIS Quarterly* (40:2), pp. 267-277 (doi: 10.25300/MISQ/2016/40:2.03).

Manokha, I. 2020. "The Implications of Digital Employee Monitoring and People Analytics for Power Relations in the Workplace," *Surveillance & Society* (18:4), pp. 540-554 (doi: 10.24908/ss.v18i4.13776).

Mantel, N., and Haenszel, W. 1959. "Statistical Aspects of the Analysis of Data From Retrospective Studies of Disease," *JNCI: Journal of the National Cancer Institute* (22:4), pp. 719-748 (doi: 10.1093/jnci/22.4.719).

March, S., and Storey, V. 2008. "Design Science in the Information Systems Discipline: An Introduction to the Special Issue on Design Science Research," *Management Information Systems Quarterly* (32:4), pp. 725-730.

March, S. T., and Smith, G. F. 1995. "Design and natural science research on information technology," *Decision support systems* (15:4), pp. 251-266 (doi: 10.1016/0167-9236(94)00041-2).

Markus, M. L., and Silver, M. 2008. “A Foundation for the Study of IT Effects: A New Look at DeSanctis and Poole’s Concepts of Structural Features and Spirit,” *Journal of the Association for Information Systems* (9:10), pp. 609-632 (doi: 10.17705/1jais.00176).

Marreiros, G., Santos, R., Ramos, C., and Neves, J. 2010. “Context-Aware Emotion-Based Model for Group Decision Making,” *IEEE Intelligent Systems* (25:2), pp. 31-39 (doi: 10.1109/MIS.2010.46).

Marshall, S. 2015. *A digital workplace definition*. https://www.clearbox.co.uk/a-Digital-Workplace-Definition/. Accessed 31 October 2020.

Maslach, C., and Jackson, S. E. 1986. *Maslach Burnout Inventory,* Palo Alto, CA: Consulting Psychologist Press.

Maslach, C., Schaufeli, W. B., and Leiter, M. P. 2001. “Job burnout,” *Annual Review of Psychology* (52), pp. 397-422 (doi: 10.1146/annurev.psych.52.1.397).

Massot, B., Baltenneck, N., Gehin, C., Dittmar, A., and McAdams, E. 2012. “EmoSense: An Ambulatory Device for the Assessment of ANS Activity—Application in the Objective Evaluation of Stress With the Blind,” *IEEE Sensors Journal* (12:3), pp. 543-551 (doi: 10.1109/JSEN.2011.2132703).

Mayya, S., Jilla, V., Tiwari, V. N., Nayak, M. M., and Narayanan, R. 2015. “Continuous monitoring of stress on smartphone using heart rate variability,” in *2015 IEEE 15th International Conference on Bioinformatics and Bioengineering (BIBE),* Belgrade, Serbia. 2015, IEEE, pp. 1-5.

Mazmanian, M. 2013. “Avoiding the Trap of Constant Connectivity: When Congruent Frames Allow for Heterogeneous Practices,” *Academy of Management Journal* (56:5), pp. 1225-1250 (doi: 10.5465/amj.2010.0787).

McFatter, R. M. 1979. “The Use of Structural Equation Models in Interpreting Regression Equations Including Suppressor and Enhancer Variables,” *Applied Psychological Measurement* (3:1), pp. 123-135 (doi: 10.1177/014662167900300113).

Megginson, L. C. 1963. “Lessons from Europe for American business,” *The Southwestern Social Science Quarterly* (44:1), pp. 3-13.

Melville, Kraemer, and Gurbaxani 2004. “Review: Information Technology and Organizational Performance: An Integrative Model of IT Business Value,” *MIS Quarterly* (28:2), p. 283 (doi: 10.2307/25148636).

Merriam-Webster n.d. *Information technology*. https://www.merriam-webster.com/dictionary/information%20technology. Accessed 18 December 2020.

Meth, H., Mueller, B., and Maedche, A. 2015. "Designing a Requirement Mining System," *Journal of the Association for Information Systems* (16:9), pp. 799-837 (doi: 10.17705/1jais.00408).

Meulendijk, M., Meulendijks, E., Jansen, P., Numans, M., and Spruit, M. 2014. "What Concerns Users of Medical Apps? Exploring Non-Functional Requirements of Medical Mobile Applications," in *Proceedings of the European Conference on Information Systems*.

Miller, G. A. 1956. "The magical number seven, plus or minus two: some limits on our capacity for processing information," *Psychological Review* (63:2), pp. 81-97 (doi: 10.1037/h0043158).

Miller-Merrell, J. 2012. "The workplace engagement economy where HR, social, mobile, and tech collide," *Employment relations today* (39:2), pp. 1-9 (doi: 10.1002/ert.21359).

Mingers, J. 2001. "Combining IS Research Methods: Towards a Pluralist Methodology," *Information Systems Research* (12:3), pp. 240-259 (doi: 10.1287/isre.12.3.240.9709).

Miyamoto, S. W., Henderson, S., Young, H. M., Pande, A., and Han, J. J. 2016. "Tracking Health Data Is Not Enough: A Qualitative Exploration of the Role of Healthcare Partnerships and mHealth Technology to Promote Physical Activity and to Sustain Behavior Change," *JMIR mHealth and uHealth* (4:1), e5 (doi: 10.2196/mhealth.4814).

Mohajeri, K., Mesgari, M., and Lee, A. S. 2020. "When Statistical Significance is not Enough: Investigating Relevance, Practical Significance, and Statistical Significance," *Management Information Systems Quarterly* (44:2), pp. 525-559 (doi: 10.25300/MISQ/2020/13932).

Mohino-Herranz, I., Gil-Pita, R., Ferreira, J., Rosa-Zurera, M., and Seoane, F. 2015. "Assessment of Mental, Emotional and Physical Stress through Analysis of Physiological Signals Using Smartphones," *Sensors (Basel, Switzerland)* (15:10), pp. 25607-25627 (doi: 10.3390/s151025607).

Möhring, K., Naumann, E., Reifenscheid, M., Blom, A. G., Wenz, A., Rettig, T., Lehrer, R., Krieger, U., Juhl, S., Friedel, S., Fikel, M., and Cornesse, C. 2020. *Die Mannheimer Corona-Studie: Schwerpunktbericht zur Erwerbstätigkeit in Deutschland*. https://www.uni-mannheim.de/media/Einrichtungen/gip/Corona_Studie/2020-04-16_Schwerpunktbericht_Erwerbstaetigkeit.pdf. Accessed 18 December 2020.

Momeni, N., Dell'Agnola, F., Arza, A., and Atienza, D. 2019. "Real-Time Cognitive Workload Monitoring Based on Machine Learning Using Physiological Signals in Rescue

Missions," *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference* (2019), pp. 3779-3785 (doi: 10.1109/EMBC.2019.8857501).

Moore, G. C., and Benbasat, I. 1991. "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation," *Information Systems Research* (2:3), pp. 192-222 (doi: 10.1287/isre.2.3.192).

Moore, P., and Piwek, L. 2017. "Regulating wellbeing in the brave new quantified workplace," *Employee Relations* (39:3), pp. 308-316 (doi: 10.1108/ER-06-2016-0126).

Moore, P., Xhafa, F., and Barolli, L. 2014. "Semantic Valence Modeling: Emotion Recognition and Affective States in Context-Aware Systems," in *2014 28th International Conference on Advanced Information Networking and Applications Workshops*, BC, Canada. 5/13/2014 - 5/16/2014, IEEE, pp. 536-541.

Morana, S., Friemel, C., Gnewuch, U., Maedche, A., and Pfeiffer, J. 2017. "Interaktion mit smarten Systemen — Aktueller Stand und zukünftige Entwicklungen im Bereich der Nutzerassistenz," *Wirtschaftsinformatik & Management* (9:5), pp. 42-51 (doi: 10.1007/s35764-017-0101-7).

Moreau, M., Valente, F., Mak, R., Pelfrene, E., Smet, P. de, Backer, G. de, and Kornitzer, M. 2004. "Occupational stress and incidence of sick leave in the Belgian workforce: the Belstress study," *Journal of epidemiology and community health* (58:6), pp. 507-516 (doi: 10.1136/jech.2003.007518).

Mulki, J. P., Bardhi, F., Lassk, F. G., and Nanavaty-Dahl, J. 2009. "Set up remote workers to thrive," *MIT Sloan Management Review* (51:1), p. 63.

Mumford, E. 2000. "A socio-technical approach to systems design," *Requirements Engineering* (5:2), pp. 125-133.

Mumford, E. 2006. "The story of socio-technical design: reflections on its successes, failures and potential," *Information Systems Journal* (16:4), pp. 317-342 (doi: 10.1111/j.1365-2575.2006.00221.x).

Naditch, M. P., Gargan, M. A., and Michael, L. B. 1975. "Denial, anxiety, locus of control, and the discrepancy between aspirations and achievements as components of depression," *Journal of Abnormal Psychology* (84:1), pp. 1-9 (doi: 10.1037/h0076254).

Nahum-Shani, I., Hekler, E. B., and Spruijt-Metz, D. 2015. "Building health behavior models to guide the development of just-in-time adaptive interventions: A pragmatic framework," *Health Psychology* (34S:0), pp. 1209-1219 (doi: 10.1037/hea0000306).

Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., and Murphy, S. A. 2018. “Just-in-Time Adaptive Interventions (JITAIs) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support,” *Annals of behavioral medicine : a publication of the Society of Behavioral Medicine* (52:6), pp. 446-462 (doi: 10.1007/s12160-016-9830-8).

Narayanan, L., Menon, S., and Spector, P. E. 1999. “Stress in the workplace: a comparison of gender and occupations,” *Journal of Organizational Behavior* (20:1), pp. 63-73 (doi: 10.1002/(SICI)1099-1379(199901)20:1<63:AID-JOB873>3.0.CO;2-J).

Navruz, B., Capraro, R. M., Bicer, A., and Capraro, M. M. 2015. “A Review of Higher-Order Factor Analysis Interpretation Strategies,” *Journal of Measurement and Evaluation in Education and Psychology* (6:1), pp. 72-94 (doi: 10.21031/EPOD.72637).

Nayak, M. S. D. P., and Narayan, K. A. 2019. “Strengths and weakness of online surveys,” *IOSR Journal of Humanities and Social Science* (24:5), pp. 31-38 (doi: 10.9790/0837-2405053138).

Nickerson, R. C., Varshney, U., and Muntermann, J. 2013. “A method for taxonomy development and its application in information systems,” *Eur J Inf Syst* (22:3), pp. 336-359 (doi: 10.1057/ejis.2012.26).

Nilles, J. M. 1994. *Making Telecommuting Happen*: *A Guide for Telemanagers and Telecommuters*, New York: Van Nostrand Reinhold.

Ninaus, K., Diehl, S., Terlutter, R., Chan, K., and Huang, A. 2015. “Benefits and stressors - Perceived effects of ICT use on employee health and work stress: An exploratory study from Austria and Hong Kong,” *International Journal of Qualitative Studies on Health and Well-Being* (10), p. 28838 (doi: 10.3402/qhw.v10.28838).

Nisafani, A. S., Kiely, G., and Mahony, C. 2020. “Workers’ technostress: a review of its causes, strains, inhibitors, and impacts,” *Journal of Decision Systems* (61:10), pp. 1-16 (doi: 10.1080/12460125.2020.1796286).

Norman, D. A. 2013. *The design of everyday things*, New York, NY: Basic Books.

Nunnally, J. C., and Bernstein, I. H. 1994. *Psychometric Theory*, New York, NY: McGraw-Hill.

Nüske, N., Bayer, S., and Lanzl, J. 2019. “Digitization of the German Workplace: Typical Technologies and Who Uses Them,” research in process.

Ollander, S., Godin, C., Campagne, A., and Charbonnier, S. 2016. “A comparison of wearable and stationary sensors for stress detection,” in *2016 IEEE International Conference on*

Systems, Man, and Cybernetics: *Conference proceedings,* Budapest, Hungary. 10/9/2016 - 10/12/2016, Piscataway, NJ: IEEE, pp. 4362-4366.

Orlikowski, W. J., and Baroudi, J. J. 1991. "Studying Information Technology in Organizations: Research Approaches and Assumptions," *Information Systems Research* (2:1), pp. 1-28 (doi: 10.1287/isre.2.1.1).

Orlikowski, W. J., and Scott, S. V. 2015. "The Algorithm and the Crowd: Considering the Materiality of Service Innovation," *Management Information Systems Quarterly* (39:1), pp. 201-216 (doi: 10.25300/MISQ/2015/39.1.09).

Pandey, P. S. 2017. "Machine Learning and IoT for prediction and detection of stress," in *Proceedings of the 2017 17th International Conference on Computational Science and Its Applications (ICCSA)*: *03-06 July 2017, University of Trieste, Trieste, Italy,* O. Gervasi (ed.). 2017/07, [Piscataway, New Jersey]: IEEE, pp. 1-5.

Parkes, K. R. 1994. "Personality and coping as moderators of work stress processes: Models, methods and measures," *Work & Stress* (8:2), pp. 110-129 (doi: 10.1080/02678379408259984).

Patall, E. A., Cooper, H., and Robinson, J. C. 2008. "The effects of choice on intrinsic motivation and related outcomes: a meta-analysis of research findings," *Psychological Bulletin* (134:2), pp. 270-300 (doi: 10.1037/0033-2909.134.2.270).

Patel, J., Ryoo, S., and Kettinger, W. 2012. "Theorizing the dual role of information technology in technostress research," in *Proceedings of the Americas Conference on Information Systems,* Seattle, Washington, USA. August, 09.-12.

Pava, C. H. P. 1983. "Designing managerial and professional work for high performance: A sociotechnical approach," *National Productivity Review* (2:2), pp. 126-135 (doi: 10.1002/npr.4040020204).

Pearse, N. 2019. "An illustration of deductive analysis in qualitative research," in *18th European Conference on Research Methodology for Business and Management Studies,* pp. 264-270.

Peer, E., Vosgerau, J., and Acquisti, A. 2014. "Reputation as a sufficient condition for data quality on Amazon Mechanical Turk," *Behavior Research Methods* (46:4), pp. 1023-1031 (doi: 10.3758/s13428-013-0434-y).

Peeters, M. C. W., Montgomery, A. J., Bakker, A. B., and Schaufeli, W. B. 2005. "Balancing Work and Home: How Job and Home Demands Are Related to Burnout," *International Journal of Stress Management* (12:1), pp. 43-61 (doi: 10.1037/1072-5245.12.1.43).

Peffers, K., Rothenberger, M., and Kuechler, B. (eds.) 2012. *Design Science Research in Information Systems. Advances in Theory and Practice*, Berlin, Heidelberg: Springer Berlin Heidelberg.

Peffers, K., Tuunanen, T., Rothenberger, M. A., and Chatterjee, S. 2007. "A Design Science Research Methodology for Information Systems Research," *Journal of Management Information Systems* (24:3), pp. 45-77 (doi: 10.2753/MIS0742-1222240302).

Pemberton, J., and Robson, A. 1995. "The spreadsheet – just another filing cabinet?" *Management Decision* (33:8), pp. 30-35 (doi: 10.1108/00251749510093914).

Picard, R. W. 2003. "Affective computing: challenges," *International Journal of Human-Computer Studies* (59:1-2), pp. 55-64 (doi: 10.1016/S1071-5819(03)00052-1).

Picard, R. W., and Liu, K. K. 2007. "Relative subjective count and assessment of interruptive technologies applied to mobile monitoring of stress," *International Journal of Human-Computer Studies* (65:4), pp. 361-375 (doi: 10.1016/j.ijhcs.2006.11.019).

Pinder, C., Vermeulen, J., Cowan, B. R., and Beale, R. 2018. "Digital Behaviour Change Interventions to Break and Form Habits," *ACM Transactions on Computer-Human Interaction* (25:3), pp. 1-66 (doi: 10.1145/3196830).

Pioggia, G., Carbonaro, N., Anania, G., Tognetti, A., Tartarisco, G., Ferro, M., Rossi, D. de, Gaggioli, A., and Riva, G. 2010. "Interreality: The use of advanced technologies in the assessment and treatment of psychological stress," in *10th International Conference on Intelligent Systems Design and Applications (ISDA), 2010*: *Nov. 29, 2010 - Dec. 1, 2010, Cairo, Egypt ; [including workshop papers]*, A. E. Hassanien (ed.), Cairo, Egypt. 11/29/2010 - 12/1/2010, Piscataway, NJ: IEEE, pp. 1047-1051.

Pirkkalainen, H., Salo, M., Tarafdar, M., and Makkonen, M. 2019. "Deliberate or Instinctive? Proactive and Reactive Coping for Technostress," *Journal of Management Information Systems* (36:4), pp. 1179-1212 (doi: 10.1080/07421222.2019.1661092).

Plarre, K., Raij, A., Hossain, S. M., Ali, A. A., Nakajima, M., Al'Absi, M., Ertin, E., Kamarck, T., Kumar, S., Scott, M., Siewiorek, D., Smailagic, A., and Wittmers, L. E. 2011. "Continuous Inference of Psychological Stress From Sensory Measurements Collected in the Natural Environment," in *Proceedings of the ACM/IEEE International Conference on Information Processing in Sensor Networks*, pp. 97-108.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., and Podsakoff, N. P. 2003. "Common method biases in behavioral research: a critical review of the literature and recommended remedies: A Critical Review of the Literature and Recommended Remedies," *The Journal of applied psychology* (88:5), pp. 879-903 (doi: 10.1037/0021-9010.88.5.879).

Popper, K. 2005. *The logic of scientific discovery*, Routledge.

Price, D. O. 1956. "SURVEY DESIGN AND ANALYSIS: PRINCIPLES, CASES AND PROCEDURES. By Herbert Hyman with a foreword by Paul F. Lazarsfeld. Glencoe, Illinois: The Free Press, 1955. 425 pp. $7.50," *Social Forces* (35:1), p. 91 (doi: 10.2307/2573125).

Prinz, P., Hertrich, K., Hirschfelder, U., and Zwaan, M. de 2012. "Burnout, depression and depersonalisation--psychological factors and coping strategies in dental and medical students," *GMS Zeitschrift für medizinische Ausbildung* (29:1), Doc10 (doi: 10.3205/zma000780).

R Development Core Team 2019. *R: A Language and Environment for Statistical Computing*, Vienna, Austria: R Foundation for Statistical Computing.

Rachuri, K. K., Musolesi, M., Mascolo, C., Rentfrow, P. J., Longworth, C., and Aucinas, A. 2010. "EmotionSense," in *Proceedings of the ACM International Conference on Ubiquitous Computing*, pp. 281-290.

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., and Tu, Q. 2008. "The Consequences of Technostress for End Users in Organizations: Conceptual Development and Empirical Validation," *Information Systems Research* (19:4), pp. 417-433 (doi: 10.1287/isre.1070.0165).

Ranganathan, A., and Campbell, R. H. 2003. "A middleware for context-aware agents in ubiquitous computing environments," in *ACM/IFIP/USENIX International Conference on Distributed Systems Platforms and Open Distributed Processing*, Springer, pp. 143-161.

Regal, C., Gimpel, H., and Lanzl, J. 2020. "The Effects of Home Office and Telework in Times of the Covid-19 Pandemic: A Longitudinal Mixed Methods Study," *Working Paper*.

Reinecke, L., Aufenanger, S., Beutel, M. E., Dreier, M., Quiring, O., Stark, B., Wölfling, K., and Müller, K. W. 2017. "Digital Stress over the Life Span: The Effects of Communication Load and Internet Multitasking on Perceived Stress and Psychological Health Impairments in a German Probability Sample," *Media Psychology* (20:1), pp. 90-115 (doi: 10.1080/15213269.2015.1121832).

Reis, H. T., Sheldon, K. M., Gable, S. L., Roscoe, J., and Ryan, R. M. 2000. "Daily Well-Being: The Role of Autonomy, Competence, and Relatedness," *Personality and Social Psychology Bulletin* (26:4), pp. 419-435 (doi: 10.1177/0146167200266002).

Revelle, W. 2019. *Psych: Procedures for Psychological, Psychometric, and Personality Research*, Evanston, IL: Northwestern University.

Richardson, H. A., Simmering, M. J., and Sturman, M. C. 2009. "A Tale of Three Perspectives," *Organizational research methods* (12:4), pp. 762-800 (doi: 10.1177/1094428109332834).

Riedl, R. 2012. "On the biology of technostress," *ACM SIGMIS Database: the DATABASE for Advances in Information Systems* (44:1), pp. 18-55 (doi: 10.1145/2436239.2436242).

Riedl, R. 2013. "Mensch-Computer-Interaktion und Stress," *HMD Praxis der Wirtschaftsinformatik* (50:6), pp. 97-106 (doi: 10.1007/BF03342073).

Riedl, R., and Javor, A. 2012. "The biology of trust: Integrating evidence from genetics, endocrinology, and functional brain imaging," *Journal of Neuroscience, Psychology, and Economics* (5:2), pp. 63-91 (doi: 10.1037/a0026318).

Rindfleisch, A., Malter, A. J., Ganesan, S., and Moorman, C. 2008. "Cross-Sectional versus Longitudinal Survey Research: Concepts, Findings, and Guidelines," *Journal of Marketing Research* (45:3), pp. 261-279 (doi: 10.1509/jmkr.45.3.261).

Rindskopf, D., and Rose, T. 1988. "Some Theory and Applications of Confirmatory Second-Order Factor Analysis," *Multivariate behavioral research* (23:1), pp. 51-67 (doi: 10.1207/s15327906mbr2301_3).

Ringel, M., Baeza, R., Grassl, F., Panadiker, R., and Harnoss, J. 2020. "The Most Innovative Companies 2020: The Serial Innovation Imperative," Boston Consulting Group (ed.).

Robertson, J. 2015. *A definition of the digital workplace … and a journey*. https://www.steptwo.com.au/papers/digital-workplace-definition/. Accessed 18 December 2020.

Robey, D. 1996. "Research Commentary: Diversity in Information Systems Research: Threat, Promise, and Responsibility," *Information Systems Research* (7:4), pp. 400-408 (doi: 10.1287/isre.7.4.400).

Rodrigues, J. G. P., Kaiseler, M., Aguiar, A., Silva Cunha, J. P., and Barros, J. 2015. "A Mobile Sensing Approach to Stress Detection and Memory Activation for Public Bus Drivers," *IEEE Transactions on Intelligent Transportation Systems* (16:6), pp. 3294-3303 (doi: 10.1109/TITS.2015.2445314).

Rosemann, and Vessey 2008. “Toward Improving the Relevance of Information Systems Research to Practice: The Role of Applicability Checks,” *Management Information Systems Quarterly* (32:1), p. 1 (doi: 10.2307/25148826).

Ross, T., Burris, A., Oliveira, L., Arnott, B., and Araujo-Soares, V. 2015. “A Feasibility Study of the Effect of Phone-Based Feedback of Other Commuters’ Subjective Experiences on Driver Intentions to Change,” in *Design, User Experience, and Usability: Design Discourse*, A. Marcus (ed.), Cham: Springer International Publishing, pp. 548-558.

Rosseel, Y. 2012. “lavaan : An R Package for Structural Equation Modeling,” *Journal of statistical software* (48:2), pp. 1-36 (doi: 10.18637/jss.v048.i02).

RStudio Team 2019. *RStudio: Integrated Delopment Environment for R*, Boston, MA: PCB.

Ryan, R. M., and Deci, E. L. 2000. “Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being,” *American Psychologist* (55:1), pp. 68-78 (doi: 10.1037//0003-066X.55.1.68).

Ryan, R. M., and Deci, E. L. 2001. “On happiness and human potentials: a review of research on hedonic and eudaimonic well-being,” *Annual Review of Psychology* (52), pp. 141-166 (doi: 10.1146/annurev.psych.52.1.141).

Ryan, S. D., Harrison, D. A., and Schkade, L. L. 2002. “Information-Technology Investment Decisions: When Do Costs and Benefits in the Social Subsystem Matter?” *Journal of Management Information Systems* (19:2), pp. 85-127 (doi: 10.1080/07421222.2002.11045725).

S, A. A., P, S., V, S., S, S. K., A, S., Akl, T. J., P, P. S., and Sivaprakasam, M. 2020. “Electrodermal Activity Based Pre-surgery Stress Detection Using a Wrist Wearable,” *IEEE journal of biomedical and health informatics* (24:1), pp. 92-100 (doi: 10.1109/JBHI.2019.2893222).

Salai, M., Vassányi, I., and Kósa, I. 2016. “Stress Detection Using Low Cost Heart Rate Sensors,” *Journal of healthcare engineering* (2016:2), pp. 1-13 (doi: 10.1155/2016/5136705).

Salanova, M., Llorens, S., and Cifre, E. 2013. “The dark side of technologies: technostress among users of information and communication technologies,” *International journal of psychology* (48:3), pp. 422-436 (doi: 10.1080/00207594.2012.680460).

Salo, M., Makkonen, M., and Hekkala, R. 2020. “The interplay of IT users' coping strategies: Uncovering momentary emotional load, routes, and sequences,” *MIS Quarterly* (44:3), pp. 1143-1175 (doi: 10.25300/MISQ/2020/15610).

Salo, M., Pirkkalainen, H., and Koskelainen, T. 2019. “Technostress and social networking services: Explaining users' concentration, sleep, identity, and social relation problems: Explaining Users' Concentration, Sleep, Identity, and Social Relation Problems,” *Information Systems Journal* (29:2), pp. 408-435 (doi: 10.1111/isj.12213).

Sandulescu, V., and Dobrescu, R. 2015. “Wearable system for stress monitoring of firefighters in special missions,” in *2015 E-Health and Bioengineering Conference (EHB): 11/19/2015 to 11/21/2015, Iaşi, Romania*, E.-H. a. B. Conference (ed.). 2015/11, Piscataway, NJ: IEEE, pp. 1-4.

Sano, A., and Picard, R. W. 2013. “Stress Recognition Using Wearable Sensors and Mobile Phones,” in *Humaine Association Conference on Affective Computing and Intelligent Interaction*, IEEE, pp. 671-676.

Santuzzi, A. M., and Barber, L. K. 2018. “Workplace Telepressure and Worker Well-Being: The Intervening Role of Psychological Detachment,” *Occupational Health Science* (2:4), pp. 337-363 (doi: 10.1007/s41542-018-0022-8).

Sarabadani, J., Cater, M., and Compeau, D. 2018. “10 Years of Research on Technostress Creators and Inhibitors: Synthesis and Critique,” in *Twenty-fourth Americas Conference on Information Systems (AMCIS 2018)*, New Orleans, USA.

Saris, W. E., Batista-Foguet, J. M., and Coenders, G. 2007. “Selection of Indicators for the Interaction Term in Structural Equation Models with Interaction,” *Quality & Quantity* (41:1), pp. 55-72 (doi: 10.1007/s11135-005-3956-2).

Sarker, S., Ahuja, M., and Sarker, S. 2018. “Work–life conflict of globally distributed software development personnel: An empirical investigation using border theory,” *Information Systems Research* (29:1), pp. 103-126.

Sarker, S., Chatterjee, S., and Xiao, X. 2013a. “How “sociotechnical” is our IS research? An assessment and possible ways forward,” in *34th International Conference on Information 2013*.

Sarker, S., Chatterjee, S., Xiao, X., and Elbanna, A. 2019. “The Sociotechnical Axis of Cohesion for the IS Discipline: Its Historical Legacy and its Continued Relevance,” *MIS Quarterly* (43:3), pp. 695-719 (doi: 10.25300/MISQ/2019/13747).

Sarker, S., Xiao, X., and Beaulieu, T. 2013b. “Guest Editorial: Qualitative Studies in Information Systems: A Critical Review and some Guiding Principles,” *Management Information Systems Quarterly* (37:4), pp. iii-xviii.

Schaaff, K., and Adam, M. T. 2013. "Measuring Emotional Arousal for Online Applications: Evaluation of Ultra-short Term Heart Rate Variability Measures," in *Humaine Association Conference on Affective Computing and Intelligent Interaction*, IEEE, pp. 362-368.

Schlick, C., Bruder, R., and Luczak, H. 2018. *Arbeitswissenschaft*, Springer-Verlag.

Schubert, C., Lambertz, M., Nelesen, R. A., Bardwell, W., Choi, J.-B., and Dimsdale, J. E. 2009. "Effects of stress on heart rate complexity--a comparison between short-term and chronic stress," *Biological psychology* (80:3), pp. 325-332 (doi: 10.1016/j.biopsycho.2008.11.005).

Schunk, D. H. 1989. "Self-efficacy and achievement behaviors," *Educational psychology review* (1:3), pp. 173-208 (doi: 10.1007/BF01320134).

Schweitzer, L., and Duxbury, L. 2010. "Conceptualizing and measuring the virtuality of teams," *Information Systems Journal* (20:3), pp. 267-295 (doi: 10.1111/j.1365-2575.2009.00326.x).

Schyns, B., Paul, T., Mohr, G., and Blank, H. 2005. "Comparing antecedents and consequences of leader – member exchange in a German working context to findings in the US," *European Journal of Work and Organizational Psychology* (14:1), pp. 1-22 (doi: 10.1080/13594320444000191).

Scollon, C. N., and Kim-Prieto, C. 2003. "Experience Sampling: Promises and Pitfalls, Strengths and Weaknesses," *Journal of Happiness Studies* (4:1), pp. 5-34 (doi: 10.1023/A:1023605205115).

Searle, B. J., and Lee, L. 2015. "Proactive coping as a personal resource in the expanded job demands–resources model," *International Journal of Stress Management* (22:1), pp. 46-69 (doi: 10.1037/a0038439).

Sebastian, I. M., Ross, J. W., Beath, C., Mocker, M., Moloney, K. G., and Fonstad, N. O. 2017. "How Big Old Companies Navigate Digital Transformation," *MIS Quarterly Executive* (16:3), pp. 133-150 (doi: 10.4324/9780429286797-6).

Secor, A. 2010. "Social surveys, interviews, and focus groups," in *Research methods in Geography*, B. Gomez and J. P. Jones, III (eds.), John Wiley & Sons, pp. 194-205.

Sein, Henfridsson, Purao, Rossi, and Lindgren 2011. "Action Design Research," *MIS Quarterly* (35:1), p. 37 (doi: 10.2307/23043488).

Sellberg, C., and Susi, T. 2014. "Technostress in the office: a distributed cognition perspective on human–technology interaction," *Cognition, Technology & Work* (16:2), pp. 187-201 (doi: 10.1007/s10111-013-0256-9).

Shapiro, S. S., and Wilk, M. B. 1965. “An Analysis of Variance Test for Normality (Complete Samples),” *Biometrika* (52:3/4), p. 591 (doi: 10.2307/2333709).

Singh, R. R., Conjeti, S., and Banerjee, R. 2011. “An approach for real-time stress-trend detection using physiological signals in wearable computing systems for automotive drivers,” in *14th International IEEE Conference on Intelligent Transportation Systems (ITSC), 2011*: *5 - 7 Oct. 2011, Washington, DC, USA,* Washington, DC, USA. 10/5/2011 - 10/7/2011, Piscataway, NJ: IEEE, pp. 1477-1482.

Smith, A. P., and Jones, D. M. 1992. “Noise and Performance,” in *Handbook of Human Performance*, D. M. Jones and A. P. Smith (eds.), London: Academic Press, pp. 1-28.

Smith, M., Segal, R., and Segal, J. 2014. *Stress Symptoms, Signs, and Causes*: *The Effects of Stress Overload and What You Can Do About It*. http://www.helpguide.org/articles/stress/stress-symptoms-causes-and-effects.htm. Accessed 18 December 2020.

Soma Analytics 2017. *Where Science and Technology Meet to Beat Stress At Work | Soma Analytics*. https://www.soma-analytics.com/science-technology-meet-beat-stress-work/. Accessed 30 March 2019.

Somerfield, M. R., and McCrae, R. R. 2000. “Stress and coping research. Methodological challenges, theoretical advances, and clinical applications,” *American Psychologist* (55:6), pp. 620-625 (doi: 10.1037/0003-066X.55.6.620).

Sonnenberg, C., and Vom Brocke, J. 2012. “Evaluation Patterns for Design Science Research Artefacts,” in *Practical Aspects of Design Science*: *European Design Science Symposium, EDSS 2011, Leixlip, Ireland, October 14, 2011, Revised Selected Papers*, M. Helfert and B. Donnellan (eds.), Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 71-83.

Sonnentag, S., Kuttler, I., and Fritz, C. 2010. “Job stressors, emotional exhaustion, and need for recovery: A multi-source study on the benefits of psychological detachment,” *Journal of Vocational Behavior* (76:3), pp. 355-365 (doi: 10.1016/j.jvb.2009.06.005).

Srivastava, S. C., Chandra, S., and Shirish, A. 2015. “Technostress creators and job outcomes: theorising the moderating influence of personality traits,” *Information Systems Journal* (25:4), pp. 355-401 (doi: 10.1111/isj.12067).

Staples, D. S., Hulland, J. S., and Higgins, C. A. 1999. “A Self-Efficacy Theory Explanation for the Management of Remote Workers in Virtual Organizations,” *Journal of Computer-Mediated Communication* (10:6), pp. 758-776 (doi: 10.1287/orsc.10.6.758).

Statista 2010. *Stress: Selbsteinschätzung | Statistik*. https://de.statista.com/statistik/daten/studie/167423/umfrage/stress-selbsteinschaetzung/. Accessed 18 December 2020.

Steca, P., Monzani, D., Greco, A., D'Addario, M., Cappelletti, E., and Pancani, L. 2016. "The Effects of Short-Term Personal Goals on Subjective Well-Being," *Journal of Happiness Studies* (17:4), pp. 1435-1450 (doi: 10.1007/s10902-015-9651-7).

Steiger, J. H. 2007. "Understanding the limitations of global fit assessment in structural equation modeling," *Personality and Individual Differences* (42:5), pp. 893-898 (doi: 10.1016/j.paid.2006.09.017).

Strangmeier, R. 2008. "Was ist Wirtschaftsinformatik? Zum Selbstverständnis einer jungen Wissenschaft," in *Intelligent Decision Support*, Springer, pp. 447-456.

Stride, C. B., Gardner, S. E., Catley, N., and Thomas, F. 2019. "Mplus code for mediation, moderation and moderated mediation models,"

Strong, D., Volkoff, O., Johnson, S., Pelletier, L., Tulu, B., Bar-On, I., Trudel, J., and Garber, L. 2014. "A Theory of Organization-EHR Affordance Actualization," *Journal of the Association for Information Systems* (15:2), pp. 53-85 (doi: 10.17705/1jais.00353).

Sumiyana, S., and Sriwidharmanely, S. 2020. "Mitigating the harmful effects of technostress: inducing chaos theory in an experimental setting," *Behaviour & Information Technology* (39:10), pp. 1079-1093 (doi: 10.1080/0144929X.2019.1641229).

Sutanto, J., Palme, E., Tan, C.-H., and Phang, C. W. 2013. "Addressing the Personalization-Privacy Paradox: An Empirical Assessment from a Field Experiment on Smartphone Users," *MIS Quarterly* (37:4), pp. 1141-1164 (doi: 10.25300/MISQ/2013/37.4.07).

Tarafdar, M., Cooper, C. L., and Stich, J.-F. 2019. "The technostress trifecta - techno eustress, techno distress and design: Theoretical directions and an agenda for research," *Information Systems Journal* (29:1), pp. 6-42 (doi: 10.1111/isj.12169).

Tarafdar, M., Gupta, A., and Turel, O. 2013. "The dark side of information technology use," *Information Systems Journal* (23:3), pp. 269-275 (doi: 10.1111/isj.12015).

Tarafdar, M., Maier, C., Laumer, S., and Weitzel, T. 2020. "Explaining the link between technostress and technology addiction for social networking sites: A study of distraction as a coping behavior," *Information Systems Journal* (30:1), pp. 96-124 (doi: 10.1111/isj.12253).

Tarafdar, M., Pullins, E. B., and Ragu-Nathan, T. S. 2015. “Technostress: negative effect on performance and possible mitigations,” *Information Systems Journal* (25:2), pp. 103-132 (doi: 10.1111/isj.12042).

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., and Ragu-Nathan, T. S. 2007. “The Impact of Technostress on Role Stress and Productivity,” *Journal of Management Information Systems* (24:1), pp. 301-328 (doi: 10.2753/MIS0742-1222240109).

Tarafdar, M., Tu, Q., and Ragu-Nathan, T. S. 2010. “Impact of Technostress on End-User Satisfaction and Performance,” *Journal of Management Information Systems* (27:3), pp. 303-334 (doi: 10.2753/MIS0742-1222270311).

Tarafdar, M., Tu, Q., Ragu-Nathan, T. S., and Ragu-Nathan, B. S. 2011. “Crossing to the dark side,” *Communications of the ACM* (54:9), pp. 113-120 (doi: 10.1145/1995376.1995403).

Tashakkori, A., and Teddlie, C. 1998a. *Mixed methodology: Combining qualitative and quantitative approaches*, Sage.

Tashakkori, A., and Teddlie, C. 1998b. *Mixed Methodology: Combining Qualitative and Quantitative Approaches*, Thousand Oaks, CA: Sage.

Tashakkori, A., and Teddlie, C. 2003a. “Issues and dilemmas in teaching research methods courses in social and behavioural sciences: US perspective,” *International Journal of Social Research Methodology* (6:1), pp. 61-77 (doi: 10.1080/13645570305055).

Tashakkori, A., and Teddlie, C. 2003b. “The past and future of mixed methods research: From data triangulation to mixed model designs,” *Handbook of mixed methods in social and behavioral research*, pp. 671-701.

Tavakol, M., and Dennick, R. 2011. “Making sense of Cronbach's alpha,” *International Journal of Medical Education* (2), pp. 53-55 (doi: 10.5116/ijme.4dfb.8dfd).

Teddlie, C., and Tashakkori, A. 2003. “Major issues and controversies in the use of mixed methods in the social and behavioral sciences,” *Handbook of mixed methods in social and behavioral research* (1), pp. 13-50.

Thatcher, J. B., Wright, R. T., Sun, H., Zagenczyk, T. J., and Klein, R. 2018. “Mindfulness in Information Technology Use: Definitions, Distinctions, and a New Measure,” *Management Information Systems Quarterly* (42:3), pp. 831-847 (doi: 10.25300/MISQ/2018/11881).

The American Institute of Stress 2014. *50 Common Signs and Symptoms of Stress*. http://www.stress.org/stress-effects/. Accessed 18 December 2020.

Thoits, P. A. 1995. “Stress, coping, and social support processes: where are we? What next?” *Journal of Health and Social Behavior* (Spec No), pp. 53-79 (doi: 10.2307/2626957).

Þórarinsdóttir, H., Kessing, L. V., and Faurholt-Jepsen, M. 2017. “Smartphone-Based Self-Assessment of Stress in Healthy Adult Individuals: A Systematic Review,” *Journal of medical Internet research* (19:2), e41 (doi: 10.2196/jmir.6397).

Thorndike, R. L. 1953. “Who belongs in the family?” *Psychometrika* (18:4), pp. 267-276 (doi: 10.1007/BF02289263).

Tiefenbeck, V., Wörner, A., Schöb, S., Fleisch, E., and Staake, T. 2019. “Real-time feedback promotes energy conservation in the absence of volunteer selection bias and monetary incentives,” *Nature Energy* (4:1), pp. 35-41 (doi: 10.1038/s41560-018-0282-1).

Tomczak, M., and Tomczak, E. 2014. “The Need to Report Effect Size Estimates Revisited: An Overview of some Recommended Measures of Effect Size,” *Trends in Sport Sciences* (1:21), pp. 19-25.

Traina, M., Cataldo, A., Galullo, F., and Russo, G. 2011. “Effects of Anxiety Due to Mental Stress on Heart Rate Variability in Healthy Subjects,” *Minerva Psichiatr* (52:4), pp. 227-231.

Trimmel, M., Meixner-Pendleton, M., and Haring, S. 2003. “Stress response caused by system response time when searching for information on the Internet,” *Human Factors: The Journal of the Human Factors and Ergonomics Society* (45:4), pp. 615-621 (doi: 10.1518/hfes.45.4.615.27084).

Trull, T. J., and Ebner-Priemer, U. 2013. “Ambulatory assessment,” *Annual review of clinical psychology* (9), pp. 151-176 (doi: 10.1146/annurev-clinpsy-050212-185510).

Tu, Q., Wang, K., and Shu, Q. 2005. “Computer-related technostress in China,” *Communications of the ACM* (48:4), pp. 77-81 (doi: 10.1145/1053291.1053323).

Tucker, J. W. 1994. “Generalized Van der Waerden Identities,” *Journal of Physics A: Mathematical and General* (27:3), pp. 659-663.

Turel, O., and Qahri-Saremi, H. 2016. “Problematic Use of Social Networking Sites: Antecedents and Consequence from a Dual-System Theory Perspective,” *Journal of Management Information Systems* (33:4), pp. 1087-1116 (doi: 10.1080/07421222.2016.1267529).

Tzelgov, J., and Henik, A. 1991. “Suppression situations in psychological research: Definitions, implications, and applications,” *Psychological Bulletin* (109:3), pp. 524-536 (doi: 10.1037/0033-2909.109.3.524).

Unsoo, H., Changhyeon, K., Yongsu, L., Hyunki, K., Taehwan, R., and Hoi-Jun, Y. 2015. “A multimodal stress monitoring system with canonical correlation analysis,” *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference* (2015), pp. 1263-1266 (doi: 10.1109/EMBC.2015.7318597).

Urbach, N., and Ahlemann, F. 2010. “Structural Equation Modeling in Information Systems Research Using Partial Least Squares,” *Journal of Information Technology Theory and Application* (11:2), pp. 5-40.

van de Velde, D., and Hantson, P. 2011. “Technological Literacy in Youth Organisations,” in *Positioning Technology Education in the Curriculum*, Brill Sense, pp. 119-129.

Van Der Wal, Ariën J, and Shao, M. 2000. “Sensor fusion: the application of soft computing in monitoring and control for railroad maintenance,” in *Proceedings of the 3rd World Congress on Intelligent Control and Automation (Cat. No. 00EX393)*, IEEE, pp. 341-346.

van Zoonen, W., Verhoeven, J. W., and Vliegenthart, R. 2016. “Social media’s dark side: inducing boundary conflicts,” *Journal of Managerial Psychology* (31:8), pp. 1297-1311 (doi: 10.1108/JMP-10-2015-0388).

Vansteenkiste, M., Simons, J., Lens, W., Sheldon, K. M., and Deci, E. L. 2004. “Motivating learning, performance, and persistence: the synergistic effects of intrinsic goal contents and autonomy-supportive contexts: The synergistic effects of intrinsic goal contents and autonomy-supportive contexts,” *Journal of personality and social psychology* (87:2), pp. 246-260 (doi: 10.1037/0022-3514.87.2.246).

Vargha, A., Delaney, H. D., and Vargha, A. 2000. “A Critique and Improvement of the "CL" Common Language Effect Size Statistics of McGraw and Wong,” *Journal of Educational and Behavioral Statistics* (25:2), p. 101 (doi: 10.2307/1165329).

Varvogli, L., and Darviri, C. 2011. “Stress Management Techniques: Evidence-Based Procedures that Reduce Stress and Promote Health,” *Health Science Journal* (5:2), pp. 74-89.

Venable, J., Pries-Heje, J., and Baskerville, R. 2012. “A Comprehensive Framework for Evaluation in Design Science Research,” in *Design Science Research in Information Systems. Advances in Theory and Practice*, K. Peffers, M. Rothenberger and B. Kuechler (eds.), Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 423-438.

Venable, J., Pries-Heje, J., and Baskerville, R. 2016. "FEDS: a Framework for Evaluation in Design Science Research," *European Journal of Information Systems* (25:1), pp. 77-89 (doi: 10.1057/ejis.2014.36).

Venkatesh, Thong, and Xu 2012. "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," *MIS Quarterly* (36:1), p. 157 (doi: 10.2307/41410412).

Venkatesh, V., Brown, S., and Sullivan, Y. 2016. "Guidelines for Conducting Mixed-methods Research: An Extension and Illustration," *Journal of the Association for Information Systems* (17:7), pp. 435-494 (doi: 10.17705/1jais.00433).

Venkatesh, V., Brown, S. A., and Bala, H. 2013. "Bridging the Qualitative-Quantitative Divide: Guidelines for Conducting Mixed Methods Research in Information Systems," *MIS Quarterly* (37:1), pp. 21-54 (doi: 10.25300/MISQ/2013/37.1.02).

Vial, G. 2019. "Understanding digital transformation: A review and a research agenda," *The Journal of Strategic Information Systems* (28:2), pp. 118-144 (doi: 10.1016/j.jsis.2019.01.003).

Vollmann, M., and Weber, H. 2011. "Gesundheitspsychologie," in *Psychologie*: *Eine Einführung in ihre Grundlagen und Anwendungsfelder*, A. Schütz, H. Selg, M. Brand and S. Lautenbacher (eds.), Kohlhammer, pp. 394-410.

Vom Brocke, J., Riedl, R., and Léger, P.-M. 2013. "Application Strategies for Neuroscience in Information Systems Design Science Research," *Journal of Computer Information Systems* (53:3), pp. 1-13 (doi: 10.1080/08874417.2013.11645627).

Vom Brocke, J., Winter, R., Hevner, A., and Maedche, A. 2020. "Special Issue Editorial – Accumulation and Evolution of Design Knowledge in Design Science Research: A Journey Through Time and Space," *Journal of the Association for Information Systems* (21:3), pp. 520-544 (doi: 10.17705/1jais.00611).

Wagner, J., Lingenfelser, F., Baur, T., Damian, I., Kistler, F., and André, E. 2013. "The social signal interpretation (SSI) framework: multimodal signal processing and recognition in real-time," in *Proceedings of the 21st ACM international conference on Multimedia*, pp. 831-834.

Walker, M. J. 2017. "Hype Cycle for Emerging Technologies, 2017," Gartner, Inc., Stamford, Connecticut, The United States of America.

Wallace, L., Keil, M., and Rai, A. 2004. "How Software Project Risk Affects Project Performance: An Investigation of the Dimensions of Risk and an Exploratory Model*," *Decision Sciences* (35:2), pp. 289-321 (doi: 10.1111/j.00117315.2004.02059.x).

Walsham, G. 2006. "Doing interpretive research," *European Journal of Information Systems* (15:3), pp. 320-330 (doi: 10.1057/palgrave.ejis.3000589).

Wang, K., Shu, Q., and Tu, Q. 2008. "Technostress under different organizational environments: An empirical investigation," *Computers in Human Behavior* (24:6), pp. 3002-3013 (doi: 10.1016/j.chb.2008.05.007).

Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D., and Campbell, A. T. 2014. "StudentLife," in *Proceedings of the ACM International Conference on Multimedia,* Orlando, Florida, USA, pp. 3-14.

Wang, W., Kakhki, M. D., and Uppala, V. 2017. "The interaction effect of technostress and non-technological stress on employees' performance," in *Proceedings of the Americas Conference on Information Systems*: *Organizational Transformation & Information Systems (SIGORSA),* Boston, Massachusetts, USA, [S. l.]: Association for Information Systems.

Warttig, S. L., Forshaw, M. J., South, J., and White, A. K. 2013. "New, normative, English-sample data for the Short Form Perceived Stress Scale (PSS-4)," *Journal of health psychology* (18:12), pp. 1617-1628 (doi: 10.1177/1359105313508346).

Weber, R. 2012. "Evaluating and Developing Theories in the Information Systems Discipline," *Journal of the Association for Information Systems* (13:1), pp. 1-30 (doi: 10.17705/1jais.00284).

Weil, M. M., and Rosen, L. D. 1997. *Technostress: Coping with technology@ work@ home@ play,* Wiley New York.

Weinert, C., Maier, C., and Laumer, S. 2015. "Why are Teleworkes Stressed? An Ampirical Analysis of the Causes of Telework-Enables Stress," in *Wirtschaftsinformatik Proceedings 2015,* pp. 1407-1421.

Weisman, O., Chetouani, M., Saint-Georges, C., Bourvis, N., Delaherche, E., Zagoory-Sharon, O., Cohen, D., and Feldman, R. 2016. "Dynamics of Non-Verbal Vocalizations and Hormones during Father-Infant Interaction," *IEEE Transactions on Affective Computing* (7:4), pp. 337-345 (doi: 10.1109/TAFFC.2015.2478468).

Westermann, T., Möller, S., and Wechsung, I. 2015. "Assessing the Relationship between Technical Affinity, Stress and Notifications on Smartphones," in *Proceedings of the 17th*

International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '15), Copenhagen, Denmark, ACM Press, pp. 652-659.

White, M. 2012. “Digital workplaces,” *Business information review* (29:4), pp. 205-214 (doi: 10.1177/0266382112470412).

Wilcoxon, F. 1992. “Individual Comparisons by Ranking Methods,” in *Breakthroughs in Statistics*, S. Kotz and N. L. Johnson (eds.), New York, NY: Springer New York, pp. 196-202.

Williams, S. P., and Schubert, P. 2018. “Designs for the Digital Workplace,” *Procedia Computer Science* (138), pp. 478-485 (doi: 10.1016/j.procs.2018.10.066).

Winn, B., Whitaker, D., Elliott, D. B., and Phillips, N. J. 1994. “Factors affecting light-adapted pupil size in normal human subjects,” *Invest Ophthalmol Vis Sci.* (35:3), pp. 1132-1137.

Wood, W., and Neal, D. T. 2007. “A new look at habits and the habit-goal interface,” *Psychological Review* (114:4), pp. 843-863 (doi: 10.1037/0033-295X.114.4.843).

World Health Organization 1988. “Constitution of the World Health Organization,” World Health Organization (ed.), Geneva.

Wu, W., Pirbhulal, S., Zhang, H., and Mukhopadhyay, S. C. 2019. “Quantitative Assessment for Self-Tracking of Acute Stress Based on Triangulation Principle in a Wearable Sensor System,” *IEEE journal of biomedical and health informatics* (23:2), pp. 703-713 (doi: 10.1109/JBHI.2018.2832069).

Xanthopoulou, D., Bakker, A. B., Demerouti, E., and Schaufeli, W. B. 2007. “The role of personal resources in the job demands-resources model,” *International Journal of Stress Management* (14:2), pp. 121-141 (doi: 10.1037/1072-5245.14.2.121).

Xia, Y., and Yang, Y. 2019. “RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods,” *Behavior Research Methods* (51:1), pp. 409-428 (doi: 10.3758/s13428-018-1055-2).

Xiong, N., and Svensson, P. 2002. “Multi-sensor management for information fusion: issues and approaches,” *Information Fusion* (3:2), pp. 163-186 (doi: 10.1016/S1566-2535(02)00055-6).

Yalina, N. 2019. “Digital Workplace Implementation To Promote Gender Equality,” in *Proceedings of the International Conference on Research and Academic Community Services (ICRACOS 2019)*, Surabaya, Indonesia.

Yin, R. K. 2017. *Case study research and applications: Design and methods,* SAGE Publications.

Yip, B., Rowlinson, S., and Siu, O. L. 2008. “Coping strategies as moderators in the relationship between role overload and burnout,” *Construction Management and Economics* (26:8), pp. 871-882 (doi: 10.1080/01446190802213529).

Yun, H., Kettinger, W. J., and Lee, C. C. 2012. “A New Open Door: The Smartphone's Impact on Work-to-Life Conflict, Stress, and Resistance,” *International journal of electronic commerce* (16:4), pp. 121-152 (doi: 10.2753/JEC1086-4415160405).

Zeiler, M. D. 2012. “ADADELTA: An Adaptive Learning Rate Method,”

Zenk, S. N., Horoi, I., McDonald, A., Corte, C., Riley, B., and Odoms-Young, A. M. 2014. “Ecological momentary assessment of environmental and personal factors and snack food intake in African American women,” *Appetite* (83), pp. 333-341 (doi: 10.1016/j.appet.2014.09.008).

Zenonos, A., Khan, A., Kalogridis, G., Vatsikas, S., Lewis, T., and Sooriyabandara, M. 2016. “HealthyOffice: Mood recognition at work using smartphones and wearable sensors,” in *2016 IEEE International Conference on Pervasive Computing and Communication workshops (PerCom workshops)*: *14-18 March 2016,* Sydney, Australia. 2016, Piscataway, NJ: IEEE, pp. 1-6.

Zhang, J., Tang, H., Chen, D., and Zhang, Q. 2012. “deStress: Mobile and remote stress monitoring, alleviation, and management platform,” in *IEEE Global Communications Conference (GLOBECOM), 2012*: *3 - 7 December 2012 in Anaheim, CA, USA,* Anaheim, CA, USA. 12/3/2012 - 12/7/2012, Piscataway, NJ: IEEE, pp. 2036-2041.

Zhao, G., Hu, B., Li, X., Mao, C., and Huang, R. 2013. “A Pervasive Stress Monitoring System Based on Biological Signals,” in *2013 Ninth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, IIH-MSP 2013*: *16 - 18 Oct. 2013, Beijing, China,* K.-B. Jia (ed.), Beijing, China. 10/16/2013 - 10/18/2013, Piscataway, NJ: IEEE, pp. 530-534.

Zhao, J., Freeman, B., and Li, M. 2016. “Can Mobile Phone Apps Influence People's Health Behavior Change? An Evidence Review,” *Journal of medical Internet research* (18:11), e287 (doi: 10.2196/jmir.5692).

Zhao, X., Lynch, J. G., and Chen, Q. 2010. “Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis,” *Journal of Consumer Research* (37:2), pp. 197-206 (doi: 10.1086/651257).

Zhao, X., Xia, Q., and Huang, W. 2020. "Impact of technostress on productivity from the theoretical perspective of appraisal and coping processes," *Information & Management* (57:8), p. 103265 (doi: 10.1016/j.im.2020.103265).

Zubair, M., Yoon, C., Kim, H., Kim, J., and Kim, J. 2015. "Smart Wearable Band for Stress Detection," in *Proceedings of the International Conference on IT Convergence and Security*.

Zuppo, C. M. 2012. "Defining ICT in a Boundaryless World : The Development of a Working Hierarchy," *International Journal of Managing Information Technology* (4:3), pp. 13-22 (doi: 10.5121/ijmit.2012.4302).

Appendix A Analyzing the Effect of Technology Characteristics

Appendix A.1 Search Strings for Literature Research

Area	Specification	Search String
1 Technologies		(reality NEAR/4 (augmented OR virtual OR artificial) OR "Artificial Intelligence" OR "virtual environment") OR (digital NEAR/4 (device OR technology OR system OR machine OR assistant)) OR (technology NEAR/4 (new OR information OR communication) OR "ICT" OR robot* OR (crowd OR click OR smart) AND worker) OR (device NEAR/4 (wearable OR mobile OR smart) OR wearables OR (head NEAR/2 mounted NEAR/2 display) OR "hmd") OR (smartwatch OR smart NEAR/4 (watch OR phone OR glass*) OR mobile NEAR/4 (phone OR computing OR "based solution" OR business OR service) OR "pda") OR (tablet NEAR/2 (computer OR PC) OR touchscreen OR laptop OR notebook OR computer)
2 NOT		child* OR smoking OR smoke* OR animal OR electromagnetic OR radiation OR base-station OR "base station" OR drug* OR electrosmog OR economic OR *oscopy* OR incontinence OR elastomer* OR polymer* OR *fiber* OR fabrication OR treatment OR therap* OR "PTSD" OR war OR trier OR financial OR "mechanic* stress*" OR "deformation* stress*" OR chemical* OR crystal* OR temperatur* NEAR/3 (high* OR low*) OR arthroplast* OR piezoelect* OR metal OR transistor* OR corrosion* OR microstructur* OR biomechanic* OR oxid* OR genom* OR composit* OR bone* OR diabet* OR road
3 Context		(work* OR occupation* OR job OR employ*)
A Outcome: Stress and Strain	General and Symptoms of Illness	strain OR stress OR complaint OR affliction OR distress OR irritation OR irritability OR discomfort OR disorder NEAR/4 (mood OR psychiatric OR sleep OR affect*) OR (mental NEAR/4 (illness OR symptom* OR satiation OR health OR tension OR disorder))
	Fatigue	fatigue OR exhaustion OR satiation
	Well-Being	affect* NEAR/4 (negative OR positive OR symptom* OR tension)) OR "well being" OR "well-being" OR wellbeing OR "irritable mood"
	Technostress Creators	(techno* NEAR/4 (invasion OR uncertainty OR overload OR unreliability OR complexity OR insecurity OR stress)) OR technostress OR Technikstress
	Stress Prevention	coping OR „Boundary Management“ OR „online intervention“ OR care OR mhealth OR "mobile health" OR mHealth OR therapy OR rehabilitation OR treatment OR screening OR "monitoring") und/oder Lernaspekte ("mobile learning" or mlearning or m-learni

B Outcome: Detachment	Usage Behavior	"phantom ringing" OR "phantom vibration" OR "internet dependency" OR "mobile dependency" OR "phone dependency" OR "technology dependency" OR "internet addiction" OR "mobile addiction" OR "phone addiction" OR "technology addiction" OR “daily interruptions” OR ringxiety OR “ringing syndrome” OR “impulsive use” OR “obsessive use” OR "invasion of privacy" OR "privacy invasion" OR "role ambiguity"
	Work-Life-Conflict	“work-home interference” OR “work-home segmentation” OR "work home conflict" OR "work-home conflict" OR "work-life balance" OR "work life balance" OR “work-life conflict” OR “life-to-work-conflict” OR “life to work conflict” OR “work-to-life-conflict” OR “work to life conflict” OR “work-family-conflict” OR “work family conflict”
C Outcome: Surveillance		(surveillance NEAR/2 (performance OR computer* OR e- OR electronic*)) OR (monitoring NEAR/2 (performance OR computer* OR e- OR electronic*)) OR "performance observation"
D Outcome: Cultural Diversity in the Workplace		((backround NEAR/2 (cultural OR ethical OR national OR management)) OR (intercultural NEAR/2 (communication OR competence OR awareness)) OR (cultural NEAR/2 (differences OR distance OR norms OR habits OR values OR customs OR gap)) OR (work NEAR/4 (migration OR migrants OR immigrants OR refugees OR discrimination OR acculturation)) OR (diversity NEAR/2 (workforce OR management OR cultural)) OR "intercultural management")
E Outcome: Cognition		((cognit* OR mental* OR informat*) NEAR/2 (load OR overload OR workload)) OR overus* OR “over-us*” OR ((cognit* OR mental*) NEAR/2 (speed OR perform* OR attent* OR inattent* OR distract* OR judg* OR evaluat* OR reason* OR comput* OR (problem NEAR/2 solv*) or (deci* NEAR/2 mak*) OR comprehend* OR alert* OR aware* OR multitask*)) OR ((cognit* OR mental*) NEAR/4 (know* OR memor* OR forget* OR interrupt* OR "executive function*" OR concentrat*))
F Outcome: Acceptance		(acceptance OR satisfaction OR willingness OR trust OR reliability OR accessibility OR preference OR compliance) AND (*stress OR strain)

Notes: Search strings to identify technology characteristics which relate to technostress and its’ outcomes; for some databases operators were adjusted due to different logic

Table 30: Search Strings for the Literature Research in the qualitative Strand

Appendix A.2 Guideline for the Expert Interviews

I. Introduction	
Introduction	Thank you very much for taking the time to participate in this interview concerning healthy work with digital technologies. You are in expert in the field and we are kindly interested in your opinion and hearing your experiences regarding this topic.
Anonymity	The interview solely serves research purposes. None of your statements are traced back to you as a person, your employees or business partners.
Documentation	Do you approve that the interview will be recorded for the purpose of documentation? Please sign the declaration of consent and the data protection declaration before the interview begins.
II. Research Questions	
General	Can you think of examples of digital technologies and media which were introduced in German companies and small and medium sized enterprises (SME) in the last couples of years? What effect did the introduction have? *(Background information)* *There are different definitions and models of stress. Stress is basically a normal and adaptive response to challenges. Stress is caused by certain triggers (stressors), e.g., excessive demands, conflicts, shift work, perfectionism. In addition, stress is associated with various reactions, such as feelings (e.g. fear, anger), behaviors (e.g. increased consumption of alcohol / nicotine, social withdrawal) and physical reactions (e.g. sweating, breathlessness), but also cognitive impairments (e.g. concentration, memory).* *However, people differ in which stressors are experienced as stressful. Whether a person experiences a situation as stressful depends heavily on how the person evaluates it, whether, for example, he sees it as personally relevant or threatening, and what "tools" or resources the person has at hand to deal with the situation. Stress does not necessarily have to be negative but can, to a certain extent, also be experienced as positive and improve performance. Stress is therefore a very individual process. In everyday language, stress often refers to the negative consequences that stressors have. (Based on the transactional model by Lazarus & Folkman, 1984)* *Technostress (respectively digital stress) refers to stress that is triggered by digital technologies and is associated with certain reactions and consequences on the physical, emotional, cognitive, and behavioral level.* *Digital technologies (also information technology (IT), information and communication technology (ICT), information systems (IS) or just called computers) enable the storage and processing of data, the transfer of information and different types of electronically mediated communication (based on Zuppo, 2012). Digital technologies can be divided into hardware, software and networks. Hardware includes, for example, workstations, laptops, tablets, projectors or smartphones. Software includes, for example, Skype for Business, Microsoft Office, Google Drive or Dropbox. Intranet or social networks belong to the generic term of networks.*
Causes	In your opinion, what causes technostress among employees? • Which technologies and media may cause stress? • Which characteristics or use cases of digital technologies may cause stress? (*Examples are that a technology often evolves or that the technology can be used in a flexible manner away from the workplace or outside of working hours.)* • Which occupational groups are particularly affected? • Do employees differ with respect to what causes technostress for example persons with different age, gender, full-time/half-time employment, care of elderly persons/children? • Do employees differ with respect to what causes technostress due to their cultural background?
Consequences	In your opinion, what are the consequences of technostress for employees? • How do these consequences manifest?

Coping	In your experience, how do employees and the company / SME handle technostress. It means how do they cope? • Do employees differ with respect to how they cope with technostress for example persons with different age, gender, full-time/half-time employment, care of elderly persons/children? • Do employees differ with respect to how they cope with technostress due to their cultural background? • Does coping differ between different digital technologies and media which are sued, are they handled differently? • Does the handling of technostress differ from other forms of stress and if so in what way?
Coping Success	How successful do you think are those strategies to cope with technostress? • What do you believe is an effective way and what is a less effective way to cope? • Is this way of coping more successful/less successful than dealing with other forms of stress? In what way?
Resources	By what means or resources, e.g. features, abilities and characteristics can the assessment of technostress and the effective handling of it be supported? *(Possible areas)* • *Organizational characteristics (autonomy, social support etc.)* • *Personal characteristics (IT-skills, self-efficacy, resilience, etc.)*
III. Structuring Variables	
Areas of Expertise	In your opinion, which areas of expertise are relevant in the examination of technostress?
Occupational Groups	In your opinion, which occupational groups should eb included in focus groups investigating technostress? Are different hierarchy levels of relevance?
Cultural Background	In your opinion, should employees with different cultural backgrounds be regarded separately in focus groups?
IV. Conclusion	
Further Information	With this question we conclude our interview. Is there anything that comes to your mind which seems important in this context which we have not talked about yet?
End Note	Thank you very much for taking the time to support the research in our project!

Table 31: Guideline for the Expert Interviews in the Qualitative Strand

Appendix A.3 Guideline for the Focus Groups

I. Introduction		**Actions and Comments**
Introduction	Today, we would like to talk about your usage of digital technologies for work. Thank you for in participating in this group session. We are kindly interested in your opinions and hearing your experiences.	• Keep it general • Don't name specific technologies, stressors, or consequences to avoid priming
Digital Technologies	Which digital technologies do you use for work? *(Background information)* *Digital technologies (also information technology (IT), information and communication technology (ICT), information systems (IS) or just called computers) enable the storage and processing of data, the transfer of information and different types of electronically mediated communication (based on Zuppo, 2012). Digital technologies can be divided into hardware, software and networks. Hardware includes, for example, workstations, laptops, tablets, projectors or smartphones. Software includes, for example, Skype for Business, Microsoft Office, Google Drive or Dropbox. Intranet or social networks belong to the generic term of networks.*	• Individual work (5 mins) • Avoid "at the workplace" use "work" • Participants write down what comes to their mind without evaluation or judgement of importance, relevance, or frequency • Collect cards, spread them out on the floor and stack duplicates on top of each other (3 mins)
II. Research Questions		**Actions and Comments**
Stress	How much do(es) the named technology(ies) stress you out?	• Scale from *"not at all"* to "*totally*" • Each participant gets sticky points for the rating to glue them on the pin board (10 mins)

Causes	What usage and/or characteristics of this specific technology stresses you out exactly?	• Group discussion
		• Comparison of triads:
		    ○ 2 "less stressful" technologies vs. 1 "highly stressful" technology
		    ○ 3 heterogeneously stressful technologies
		    ○ Other interesting combinations
		• Moderator puts characteristics on pin board

Stress, Potential Characteristics	How strongly do these specific aspects stress you out? How strongly does this aspect stress you compared to the others?	• Template with the results from the afore steps is put on pin board • Moderators explains already known techno stressors • Group discussion (15 mins) • Participants get sticky points to glue them behind the characteristics on the pin board • Moderators lets participants prioritize the characteristics according to the rating
Consequences	What triggers this in you and your environment? (besides feeling stressed) What can you observe in your colleagues? How does it manifest itself in behavior (at work, at home, among friends...)? *(Additional Question)* • *Are there positive aspects?*	• Participants write on cards for each characteristic • Show matrix afterwards (short/long term consequences, psychological/physiological…) • Leave room for group discussion (15 mins) • Moderator should ask to be more precise and specific if necessary
Coping	What can you personally do about it (meaning cope with it)? What can the organization/environment do about it? What can be done about it from a technological point of view? What are your experiences / wishes here?	• Do not skip! Essential part for the participants and company's' motivation that their employees take part in the focus group • Group discussion (15 mins)
III. Conclusion		**Actions and Comments**
Further Information	With this question we conclude our workshop. Is there anything that comes to your mind which seems important in this context which we have not talked about yet?	
End Note	Thank you very much for taking the time to support the research in our project!	

Table 32: Guideline for the Focus Groups in the Qualitative Strand

Appendix A.4 Items of the Finale Scales

Construct	Item	Mean	SD	Est	Source
Usefulness	Use of {selected technology} enables me to accomplish tasks more quickly.	2.97	1.14	0.82	Ayyagari et al. 2011
	Use of {selected technology} improves the quality of my work.	2.65	1.18	0.83	
	Use of {selected technology} makes it easier to do my job.	2.88	1.13	0.90	
	Use of {selected technology} enhances my effectiveness on the job.	2.75	1.16	0.89	
Simplicity of Use (Complex-ity)	Learning to use {selected technology} is easy for me.	3.21	0.95	0.87	Ayyagari et al. 2011
	{selected technology} is easy to use.	3.20	0.95	0.92	
	It is easy to get results that I desire from {selected technology}.	3.01	0.99	0.80	
Reliability	The features provided by {selected technology} are dependable.	2.93	0.95	0.91	Ayyagari et al. 2011
	The capabilities provided by {selected technology} are reliable.	2.93	0.94	0.93	
	{selected technology} behaves in a highly consistent way.	2.92	0.96	0.86	
Anonymity	It is easy for me to hide how I use {selected technology}.	1.85	1.22	0.80	Ayyagari et al. 2011
	I can remain anonymous when using {selected technology}.	1.79	1.29	0.80	
	It is easy for me to hide my {selected technology} usage.	1.72	1.23	0.92	
	It is difficult for others to identify my use of {selected technology}.	1.75	1.22	0.76	
Mobility	The use of {selected technology} is not limited to the workplace.	2.68	1.42	0.76	Self-developed with input from Tarafdar et al. 2017
	The use of {selected technology} is not restricted to a certain location.	2.61	1.44	0.86	
	It is possible to use {selected technology} on the go.	2.53	1.50	0.93	
	{selected technology} is accessible from anywhere.	2.51	1.43	0.89	
	{selected technology} enables me to work anywhere.	2.40	1.41	0.80	
Reachability (Presenteeism)	The use of {selected technology} enables others to have access to me.	2.69	1.31	0.92	Ayyagari et al. 2011
	{selected technology} makes me accessible to others.	2.67	1.32	0.95	
	The use of {selected technology} enables me to be in touch with others.	2.74	1.29	0.95	
	{selected technology} enables me to access others.	2.77	1.28	0.95	

Construct	Item	Mean	SD	Est	Source
Pace of Change	I feel that there are frequent changes in the features of {selected technology}.	1.82	1.24	0.92	Ayyagari et al. 2011
	I feel that characteristics of {selected technology} change frequently.	1.74	1.20	0.94	
	I feel that the capabilities of {selected technology} change often.	1.78	1.22	0.94	
	I feel that the way {selected technology} works changes often.	1.70	1.21	0.92	
Pull	{selected technology} displays information only when I actively interact with it.	2.04	1.29	0.75	Self-developed
	To receive information through {selected technology} I need to actively request it.	2.03	1.35	0.83	
	Information is provided by {selected technology} only on request.	2.11	1.33	0.85	
Push	{selected technology} displays information. whilst I am otherwise engaged.	2.36	1.18	0.75	Self-developed
	I automatically receive news / through information {selected technology} when I use it.	2.48	1.13	0.89	
	{selected technology} uses push notifications to provide information.	2.59	1.15	0.74	
Intangibility of Results	The result of my work with {selected technology} is not tangible.	1.53	1.27	0.89	Self-developed
	The result of my work with {selected technology} is not clearly visible.	1.55	1.25	0.90	
	{selected technology} creates products that are not tangible.	1.56	1.26	0.84	
	The result of working with {selected technology} is not noticeable.	1.46	1.24	0.88	
	Results from the use of {selected technology} are not visible to third parties.	1.69	1.27	0.65	
	Third parties can not immediately see changes caused by using {selected technology}.	1.89	1.26	0.60	

Notes: Item means, standard deviation and factor loadings of the final scales for the characteristics of DTM; n = 4,560

Table 33: Finale Scale for the Characteristics of DTM

Appendix A.5 Taxonomy of DTMs

Category	Technology	Category	Technology
Standard Technologies	Laptop	Subject-Specific Applications	Product Development
	PC		Design Software
	Telephone		Simulation Software
	Mobile		Statistics Software
	Smartphone		Medical Software
	Tablet		Database
	Printer	Management- and Enterprise-Applications	Management Information Software
	Headset		Decision Support Systems
New Technologies	Artificial Intelligence		Administrative Software
	Augmented Reality	Payment Transaction and E-Commerce	Cash Systems
	Language Interaction		Digital Cash
Standard Applications	Office Software		E-Commerce
	Knowledge Management	Networks	Wireless Network
	Internet		Network Hardware
	CMS	Production and Logistics	Production Planning
Communication, Interaction and Collaboration	E-Mail		Manufacturing System
	Realtime Communication		Logistics System
	Social Collaboration	Environmental Recognition	Sensor Systems
	Cloud Computing		Localization
Security	Security Background		
	Security Interaction		

Table 34: Taxonomy of Digital Technologies

Appendix A.6 Rotated Components Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
I1	0.81									
I2	0.84									
I3	0.90									
I4	0.90									
I5		0.91								
I6		0.89								
I7		0.61								
I8			0.89							
I9			0.95							
I10			0.80							
I11				0.75						
I12				0.86						
I13				0.94						
I14				0.73						
I15					0.77					
I16					0.91					
I17					0.93					
I18					0.86					
I19					0.71					
I20										
I21						0.93				
I22						0.96				
I23						0.94				
I24						0.94				
I25							0.92			
I26							0.95			
I27							0.91			
I28							0.91			
I29								0.67		
I30										
I31								0.75		
I32								0.91		
I33									0.65	
I34									0.92	
I35									0.72	
I36										0.85
I37										0.87
I38										0.81
I39										0.86
I40										0.75
I41										0.68

Notes: Used extraction method was a principal axis factoring with oblimin rotation; n = 2,280

Table 35: Rotated Factor Matrix from First Sample

Appendix A.7 Latent Correlations of the Constructs in the Study

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Anonymity	**0.82**														
Intangibility	0.30	**0.80**													
Mobility	0.26	0.08	**0.85**												
Pace of Change	0.40	0.36	0.30	**0.93**											
Pull	0.17	0.11	0.20	0.25	**0.80**										
Push	0.29	0.28	0.42	0.44	0.13	**0.81**									
Reachability	0.12	0.12	0.32	0.19	0.13	0.49	**0.94**								
Reliability	0.19	-0.14	0.18	-0.13	0.24	0.12	0.28	**0.90**							
Simplicity of Use	0.10	-0.14	0.21	-0.15	0.20	0.12	0.35	0.67	**0.87**						
Usefulness	0.21	-0.09	0.18	0.10	0.22	0.23	0.33	0.52	0.44	**0.86**					
Techno-Complexity	0.11	0.38	0.00	0.29	0.02	0.14	-0.03	-0.24	-0.35	-0.12	**0.81**				
Techno-Insecurity	0.22	0.34	0.09	0.34	0.06	0.25	0.03	-0.12	-0.25	-0.02	0.65	**0.76**			
Techno-Invasion	0.24	0.39	0.13	0.36	0.04	0.27	0.03	-0.14	-0.22	-0.02	0.62	0.72	**0.78**		
Techno-Overload	0.07	0.31	0.04	0.28	0.06	0.15	-0.01	-0.17	-0.25	-0.11	0.67	0.73	0.66	**0.82**	
Techno-Uncertainty	0.21	0.22	0.12	0.37	0.09	0.25	0.08	-0.05	-0.15	0.03	0.42	0.63	0.47	0.56	**0.80**

Notes: Latent correlations of the constructs in the study obtained from confirmatory factor analysis of the constructs; square root of the AVE printed in the diagonal; n = 4,560

Table 36: Latent Correlations of the Constructs and Square Root of the AVE

Appendix A.8 Results of the Structural Model

TS Creator / Characteristic	Techno-Complexity			Techno-Insecurity			Techno-Invasion			Techno-Overload			Techno-Uncertainty		
	Est	*t*	*p*	Est	*t*	*p*	Est	*t*	*p*	Est	*t*	*p*	Est	*t*	*p*
Anonymity	-0.16	-1.56	.12	-0.27	-2.62	.01	-0.40	-3.84	.00	-0.10	-0.98	.33	-0.17	-1.63	.10
Intangibility	0.16	2.78	.01	0.34	5.97	.00	0.31	5.55	.00	0.25	4.41	.00	0.30	5.26	.00
Mobility	0.08	1.80	.07	0.18	4.15	.00	0.28	6.50	.00	0.12	2.76	.01	0.14	3.12	.00
Pace of Change	-0.04	-0.52	.60	0.04	0.50	.61	0.31	3.80	.00	0.10	1.23	.22	0.07	0.89	.37
Pull	-0.16	-1.24	.21	-0.18	-1.39	.17	-0.40	-3.10	.00	-0.23	-1.73	.08	-0.17	-1.29	.20
Push	0.11	1.03	.30	-0.08	-0.80	.42	-0.28	-2.66	.01	-0.14	-1.35	.18	0.03	0.27	.79
Reachability	-0.20	-2.33	.02	-0.16	-1.91	.06	-0.18	-2.12	.03	-0.13	-1.58	.11	-0.17	-2.08	.04
Reliability	-0.18	-1.12	.26	-0.25	-1.55	.12	-0.46	-2.87	.00	-0.07	-0.40	.68	0.11	0.72	.47
Simplicity of Use	0.08	0.49	.63	-0.19	-1.10	.27	0.40	2.33	.02	-0.18	-1.05	.30	-0.50	-2.87	.00
Usefulness	0.00	0.00	1.00	0.22	2.60	.01	0.14	1.67	.09	0.11	1.35	.18	0.07	0.80	.42

Notes: Standardized regression weights, test statistics and p-values of the structural model; n = 4,560

Table 37: Evaluating the Influence of Profiles of DTM on Technostress

Appendix B Analyzing the Effect of Autonomy Features

Appendix B.1 Screenshots of the Measurement Instrument

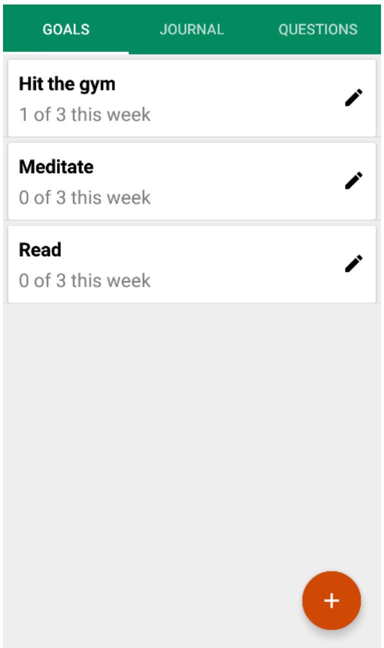


Figure 25: Goals Tab

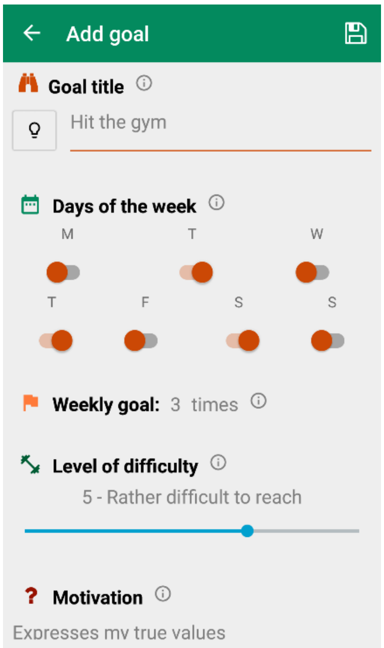


Figure 26: Add Goals Menu

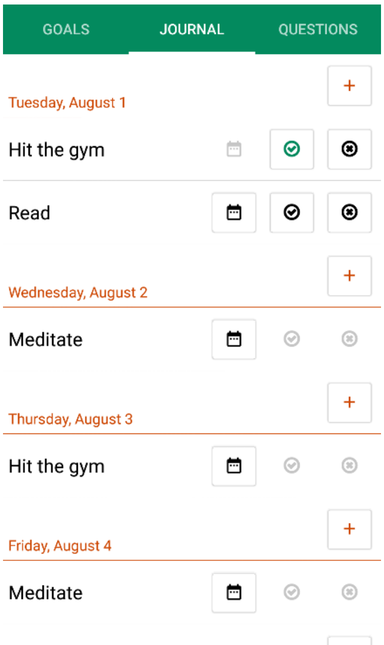


Figure 27: Journal Tab

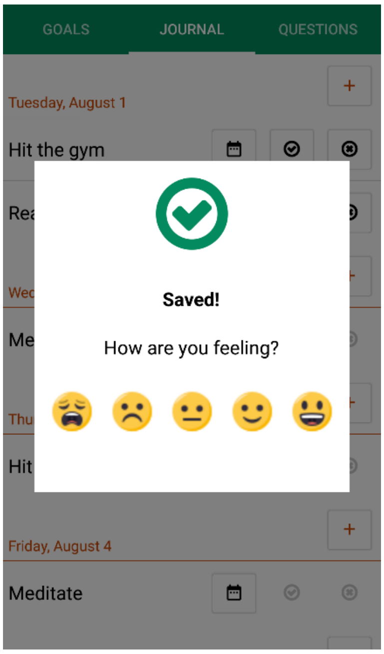


Figure 28: Screen for Indicating the Feeling after Logging

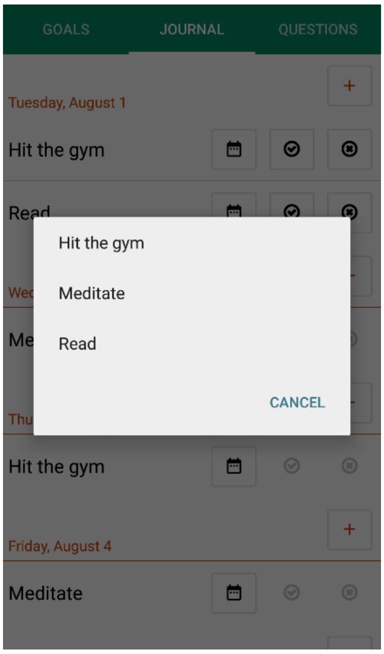


Figure 29: Screen for Spontaneously Adding an Activity

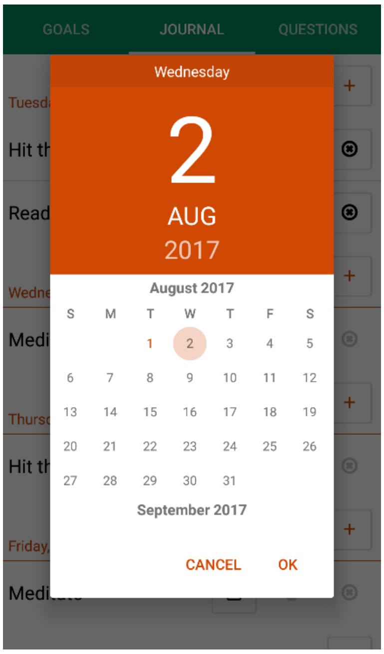


Figure 30: Screen for Moving an Activity

Appendix C Analyzing the Effect of Contextual Factors

Appendix C.1 Methodological Approach within the Qualitative Strand

For the first strand, a qualitative, interpretive approach to study the effect of the COVID-19 pandemic on German employees was adopted and data collection and analysis were guided by several principles (Glaser and Strauss 2017; Sarker et al. 2013b; Walsham 2006). These enabled us to deal with the analysis and interpretation of the data reflectively and supported us in presenting them transparently. The result was an understanding of what general changes the increased telework induced by the COVID-19 pandemic has had on the work activities of employees and what potential factors have an impact on them to check for applicability of theoretical perspective to work during COVID-19 induced social distancing.

Journalistic Articles

We analysed journalistic articles published from 18 March 2020 to 16 April of 2020 in high-quality German daily or weekly newspapers. The articles either describe the far-reaching influence of the COVID-19 pandemic on the German workforce in general or present the effect of the pandemic based on stories of multiple real people (see Table 39 for the list of articles). In this period, the lockdown (i.e., cancellation of events, contact restrictions, compulsory masks, closed restaurants, and shops) due to the COVID-19 pandemic has already been triggered and the people in Germany had a chance to get used to it.

Newspaper	Article Date	Article Title (translated)	Short Description
Tagesspiegel	03/18/2020	What you should pay attention to in everyday life during teleworking	This article describes the challenges of teleworking and how they can be addressed.
Frankfurter Allgemeine	03/20/2020	What Corona changes - Stress test for everyday working life	This article describes the working life of five employees from different industries and how it has changed during the COVID-19 pandemic.
Die Zeit	03/24/2020	How the Corona crisis will change the way we work	This article describes, in general terms, the impact of the COVID-19 pandemic on employees and what should be considered when performing telework.
Die Welt	04/03/2020	At 18 o'clock, cocktails are drunk via Skype	This article describes, in general terms, the impact of the COVID-19 pandemic on employees and the positive experiences in dealing with the challenges it poses.
Handelsblatt	04/08/2020	Home office, reduced hours, layoffs: This is how Corona changes the world of work	This article describes the working life of 8 imaginary persons representing different categories of employees and what has changed for them during the COVID-19 pandemic.
Süddeutsche Zeitung	04/16/2020	How the Corona crisis is changing the world of work	This article describes, in general terms, the impact of the COVID-19 pandemic on employees and what should be considered when performing telework.

Table 38: Analysed Articles in German Daily and Weekly Newspapers

The analysis of the journalistic articles was primarily conducted by the first author of the manuscript using open and axial coding techniques to identify important pieces of information and to analyse the relationship between them. The following labelling and relabelling of the relevant concepts were performed by all three authors in a constant comparative analysis, ending when theoretical saturation occurred (Glaser and Strauss 1967). In other words, the pieces of information were either categorized as demands or resources (i.e., change in job demands, private demands, and resources) affected by the COVID-19 induced fostering of telework or contextual aspects that could potentially influence if and how teleworking affects a demand or resource. The results of this analysis built the ground for the interviews.

Interviews

Two researchers of the author team were involved in the interviews. Interviewees were either employees or experts on the fields of human resources, IT-support, or occupational health management and hence, were well aware of the effect of the COVID-19 pandemic. The interviews aim to foster the understanding of social distancing during the COVID-19 pandemic on employee's stress and technostress and to determine the relationship to contextual aspects that influence these relationships. Additionally, the interviews with experts were used as an applicability check (i.e., the relevance of our research for practice (Rosemann and Vessey 2008)).

We conducted interviews with five employees and three experts, each lasting at least thirty minutes (see Table 39 for a list of all interviewees). Interviews were recorded and subsequently transcribed. Field notes were also taken during the interviews. To supplement the data from the interview, we added information on the personal- and job-related background of the interviewees (e.g., childcare, remote office experience, technology use). In the first part of the interview, respondents were asked to describe their everyday working life before the COVID-19 pandemic. Particular attention was paid to aspects that were already identified as relevant in journalistic articles (e.g., workplace equipment, communication behaviour, structure in everyday life). Afterward, the interviewees were asked to explain how their everyday working life is during the lockdown and what the most significant changes are compared to before. In the second part of the interview, the respondents were asked to go into more detail about the challenges they have faced in dealing with the changed conditions and what has helped them personally in dealing with them.

ID	Role	Sector	Job Description
Exp1	Expert	Occupational health management	Consultant Psychological Risk Assessment
Exp2	Expert	Research	Head of IT-Department
Exp3	Expert	Customer acquisition and customer retention	Head of HR
Emp1	Employee	Consulting of small- and medium-sized enterprises	Consultant
Emp2	Employee	Governmental Consulting	Researcher
Emp3	Employee	Pharmacy	Teamlead HR-Marketing
Emp4	Employee	Education	Teacher
Emp5	Employee	Software Development	Web Developer

Table 39: Conducted Semi-Structured Interviews with Experts and Employees

The interviews were analysed iteratively primarily by two authors of the manuscript by refining and enriching the first part of the qualitative phase using open and axial coding techniques. The following labelling and relabelling of the relevant concepts were performed by all three authors in a constant comparative analysis, ending when theoretical saturation occurred (Glaser and Strauss 1967). In particular, the information from the first part of the interview helped to identify demands and resources affected by the increasing intensity of telework. In contrast, part two broadened the understanding of different contextual aspects and their influences on employee's stress in general and technostress in particular.

The results of this analysis build the ground for our hypotheses.

Appendix C.2 Methodological Approach within the Quantitative Strand

For the second strand, a quantitative, positivistic approach was applied to test the developed hypotheses from the qualitative strand. This strand is based on data from two surveys. The first took place in March 2019 and gathered data from a representative sample of German workers on job and private demands and resources focusing on digital work, DTM use, and technostress. In May 2020, we returned to the participants sampled in 2019 from the first survey to conduct a second survey on individual level demands and resources in times of the COVID-19 pandemic. The result was the validation of the hypotheses established in the qualitative phase. Hence, we revealed changes in the work activities of employees and the effect of contextual factors on the changes in the overall technostress and on the individual technostress creators.

Survey Design and Procedures

Both surveys are based on constructs of the job-demand resources model using existing scales. It included the following aspects: digital workplace, the extent of stress factors, technostress, competence in handling digital technologies and media, organizational and social conditions at the workplace, and health status. In addition, the participants in the survey were asked about other work-related aspects, measures for dealing with stress, characteristics of the digital technologies and media used, demographic characteristics, and information about their occupation.

In the second survey, questions regarding technostress were asked again and also additionall demographic and job-related information. Furthermore, specific questions on the COVID-19 pandemic, such as their attitude towards the pandemic and how the employers handels it. Additionally, more specific questions were asked about the private situation of the participants.

In both surveys, we acquired participants via an external research panel focusing on the German workforce. Respondents were paid a small incentive for participation in the study. For the questionnaire, we collected existing item scales. For the first survey, 5,005 complete respondents were collected with good data quality (e.g., reasonable answers on work experience compared to age, actual working hours compared to contractually fixed working hours, free text fields, and finished the questionnaire in a realistic timeframe). Of those 5,005 participants, 1,553 also took part in the second survey in May 2020. From these, we excluded 195 respondents as they changed position or employer since the first survey and 341 as they were affected by job termination, reduced working hours, or other special leave due to the COVID-19 pandemic and the along going recession. Thus, our final sample consisted of 1,017 respondents, of which 43% are female and 57% are male. Table 40 provides an overview of all constructs.

Category	Construct	Items	Before	During
Contextual Factor	Child and Elderly Care (self developed)	2	38 %	
	Home office experience (self developed)	1	8.9 %	
	Manager Position (self developed)	1	44 %	
	Remote Working Self-Efficacy (Staples et al. 1999)	4	2.64	
Job Demand	Emotional demands (Burr et al. 2019)	2	2.073	1.832
	Social conflicts (Burr et al. 2019)	4	0.913	0.779
	Workload (Burr et al. 2019)	3	2.255	1.940
Techno-stress	Techno-Complexity (Ragu-Nathan et al. 2008)	5	1.065	1.085
	Techno-Insecurity (Ragu-Nathan et al. 2008)	5	1.054	0.937
	Techno-Invasion (Ragu-Nathan et al. 2008)	3	0.973	1.055
	Techno-Overload (Ragu-Nathan et al. 2008)	4	1.476	1.411
	Techno-Uncertainty (Ragu-Nathan et al. 2008)	4	1.735	1.474
Job Outcome	Productivity (Chen and Karahanna 2014)	4	2.614	2.516
Job Resource	Autonomy (Burr et al. 2019)	5	2.428	2.401
	Feedback (Burr et al. 2019)	2	1.849	1.804
	Job support (Burr et al. 2019)	4	2.428	2.426
	Leadership behaviour (Schyns et al. 2005)	6	2.431	2.440
	Sense of community (Burr et al. 2019)	2	2.906	2.966
	Technical support provision (Ragu-Nathan et al. 2008)	3	2.646	2.609
Private Demand	Emotional Home Demands (Peeters et al. 2005)	3	1.350	1.407
	Financial Worries (Fehm 1999)	4	1.021	1.135
	Mental Home Demands (Peeters et al. 2005)	4	2.017	2.081
	Quantitative Home Demands (Peeters et al. 2005)	3	1.691	1.767
Private Resource	Family Support (adapted from Burr et al. (2019))	5	2.857	2.786
	Social support (adapted from Burr et al. (2019))	2	2.594	2.634

Notes: The columns "before" and "during" refer to lockdown and the average value for this variable during a period across all participants; items were collected in English and then translated into German; n = 1,017

Table 40: Mean Values for each Construct Before and During the Lockdown

Hypotheses Testing

Before we go into detail in the validation of the hypotheses, it is necessary to check the distribution of the dependent variables (e.g., workload, technostress). This will influence the choice of further applied statistical tests. For this purpose, we performed a test for normal distribution applying the Shapiro-Wilk-Test (Shapiro and Wilk 1965). All results delivered a p-value smaller than 0.001, and therefore, a normal distribution cannot be assumed. Hence, we use non-parametric methods in the following course of analysis.

When evaluating hypotheses 1a, 1b, 2a, 2b, 3, and 4 the aim is to examine how variables have changed compared to the time before and after the lockdown. For this, we apply a Wilcoxon signed-rank test, which applies to paired samples that do not have a normal distribution (Wilcoxon 1992) and additionally calculate Wilcoxon R to report the effect size (Tomczak and Tomczak 2014). Finally, we report all changes of variables compared to before and after the lockdown where the change is statistically significantly different from zero at the 5% level and additionally, the values for all technostress creators since this is the focus of this research. Besides, we inform on the effect size and highlight values greater or equal to 0.1 (Fritz et al. 2012), to reflect both statistical and practical significance (Mohajeri et al. 2020) to answer our hypotheses.

For the remaining hypotheses 4, 5, 6, and 7 we aim to explore how technostress and the technostress creators have changed compared to the time before the lockdown. In particular, we consider the influence of different contextual factors on these changes and the extent to which these factors explain the shift in overall technostress and individual technostress creators. The different contextual factors thereby serve as group variables with different manifestations and each participant belongs to exactly one manifestation for each group variable. It is, therefore, necessary to analyse the influence of a person's membership within a group variable on the temporal change of technostress. Here we are in a classic mixed design where we have a between variable (the group membership) and a within variable (the two measurement points, before the lockdown and during the lockdown per person). As we know from previous analyses, technostress and its creators are not normally distributed, non-parametric methods must be applied. The generalized van der Waerden test is appropriate here (Tucker 1994). For all interaction effects found to be significant ($p < 0.05$) between the group and the time variable in this test, further analyses were performed in two steps.

First, we calculated the effect size of the group differences for each point in time (i.e., once before the lockdown and once during the lockdown). As a measure for the effect size, we chose Vargha et al. (2000) *A*, which is well suited for our case and allows for an intuitive interpretation. *A* is a measure that ranges from 0 to 1. Having a value of 0.5, the two groups that are being compared perform equally. Having a value of less than 0.5, the first group performs worse, and when *A* is more than 0.5, vice versa. Hence, the closer the value for *A* to 0.5 is, the smaller is the difference between the groups. More precisely, Vargha and Delaney's *A* provides the information, how often, on average, one group outperforms the other. For example, if we have a value of 0.31 for *A*, group 1 performs worse than group 2. Naturally spoken, in 31% of the time, group 1 will perform better than group 2. Equivalently, 66% of the time, group 2 will perform better than group 1. Thus, Vargha et al.'s (2000) *A* allows us to examine how the relationship between the groups changed over time (i.e., converged or diverged).

Finally, we create interaction graphs based on these results, using the estimated marginal means, to also allow for a graphical interpretation.

Appendix C.3 Elaboration of Decision Choice of Mixed-Methods Study

Step	Property	Decision Consideration	Other design decision(s) likely to affect current decision	Design decision and reference to the decision tree
Step1: decide on the appropriateness of mixed-methods research	Research Question	Qualitative or quantitative method alone was not adequate for addressing the research question. Thus, we used a mixed-methods research approach	None	Identify the research objectives supporting the research questions • We first wrote the qualitative and quantitative research objectives separately and then the mixed-methods research objective. • The qualitative research objective was: "What demands and resources of the workforce were affected by the effort for physical distancing fostering telework?" • The mixed-methods research objective was: "Are the factors identified in the qualitative study supported by the results in the quantitative study?" • The quantitative research objective was: "How have the demands and resources changed and how to do different contextual factors influence the effect of the COVID-19 pandemic on technostress?"
	Purpose of mixed-methods research	The purpose of our mixed-methods design was to help develop a research model for empirical testing using the results of the qualitative study given the lack of current research on the effect of the COVID-19 pandemic on technostress.	Research questions	Developmental purpose and the results from the qualitative strand were used to develop the research model in the quantitative strand.
	Epistemological perspective	The qualitative and quantitative components of the study used different paradigmatic assumptions.	Research questions, purpose of mixed-methods	Multiple paradigm stance.
	Paradigmatic assumptions	The researchers believed in the importance of research questions and embraced various methodological approaches from different worldviews.	Research questions, purpose of mixed-methods	We used more of the interpretive and grounded-theory perspective in the qualitative study, then applied a positivist perspective, and deductively tested the developed model in the quantitative study.
Step 2: develop strategies for mixed-methods research designs	Design investigation strategy	The mixed-methods study was aimed to develop and test a theory.	Research questions, paradigmatic assumptions	• Phase 1: exploratory investigation. • Phase 2: confirmatory investigation.
	Strands/phases of research	The study involved multiple phases.	Purpose of mixed-methods research	Multistrand design.
	Mixing strategy	The qualitative and quantitative components of the study were mixed at the data-analysis and inferential stages.	Purposes of mixed-methods research, strands/phases of research	Partially mixed methods.
	Time orientation	We started with the qualitative phase, followed by the quantitative phase.	Research questions, strands/ phases of research	Sequential (exploratory) design.
	Priority of methodological approach	The qualitative and quantitative components were not equally important.	Research questions, strands/ phases of research	Dominant-less dominant design with the quantitative study being the more dominant paradigm.

Step 3: develop strategies for collecting and analyzing mixed-methods data	Sampling design strategies	The samples for the quantitative and qualitative components of the study differed, but they came from the same underlying population (parallel samples).	Design investigation strategy, time orientation	Purposive sampling for the first qualitative study given the qualitative differences in newspapers and magazines. Purposive sampling for the qualitative phase interviewing a small number of employees and experts from a large number of people affected by social distancing. Probability sampling for the quantitative study based on the participant of the previous survey.
	Data collection strategies	• Qualitative data collection in phase 1. • Quantitative data collection in phase 2.	Sampling design strategies, time orientation, strands/phases of research	• First qualitative study: content analysis of journalistic articles using open and axial coding and conducting open-ended interviews using a pre-designed guideline. • Quantitative study: closed-ended questioning (i.e., traditional survey design).
	Data analysis strategy		Time orientation, data collection strategy, strands/phases of research	Sequential qualitative-quantitative analysis.

Appendix C.4 Mixed-Method Approach and Criteria

Quality Aspects	Quality Criteria	Response to Venkatesh et al. 's (2013) guideline
Purpose of mixed method approach	Development	This study is divided into two phases: (1) qualitative study involving the analysis of six recently published journalistic articles of top German daily and weekly newspapers to understand the effect of the COVID-19 pandemic on employee's work in general and technostress in particular, followed by additional interviews to foster the understanding of the effect of social distancing during the COVID-19 pandemic on employee's stress and technostress and to identify possible contextual factors that influence these relationships, and (2) a large quantitative survey based on the population of a previously conducted survey to test the hypotheses developed in the earlier phases. The qualitative study was used to identify the contextualized variables for model development and hypotheses justification, subsequently tested in the quantitative study.
	A less-dominant qualitative followed by a sequential dominant quantitative investigation	The scope and objectives of the qualitative investigations using a set of journalistic articles and interviews with employees are very limited; it is primarily to support the quantitative investigation.
Design quality	Design adequacy	The study used a qualitative analysis of journalistic articles and qualitative interviews along with limited documentary analysis followed by a quantitative survey. This strategy of examining "raw" data from the phenomenon as a "prelude" to the larger quantitative study ensured that the research model tested using the quantitative study was relevant to the phenomenon of interest. In doing so, it sought to combine the advantages of the two approaches, achieving depth and insight into the phenomenon as well as the breadth of coverage.
		Qualitative Journalistic Articles • Selecting suitable articles: Journalistic articles of German high-quality daily and weekly newspapers that either describe the general influence of the COVID-19 pandemic on work or present the effect of the pandemic based on stories of multiple real-world person were seen as suitable. • Conduct of analysis: For the content analysis of the journalistic articles, open and axial coding techniques were used to identify relevant pieces of information and to analyse the relationship between them. *Qualitative Interviews* • Selecting suitable interviewees: The interviewees were either employees or experts on the fields of human resources, IT-support, or occupational health management and were thus seen as suitable. • Entering the field with credibility: The interviews were primarily conducted by two authors of the manuscript, who were (at the time of the study) both working on research on the digital workplace, job demands, job resources, and technostress for years. Conduct of interviews: All interviews were conducted using a pre-designed interview guideline.
	Analytical adequacy	*Qualitative Journalistic Articles* • Labelling and relabelling of the concepts by all authors after the generation of the codes by the first author. The process was iterative and roughly resembled a constant comparative analysis, ending when theoretical saturation occurred (Glaser and Strauss 1967). • Although no quantitative measure was used to determine conformance, the identification and selection of the concepts represented a consensus among the three researchers involved in data collection and analysis, implying some form of convergence and/or reliability. • Given the exploratory nature of the study that aimed for discovery by engaging with "raw" data and the limited scope of the qualitative strand, the notion of theoretical validity is not applicable here. *Qualitative Interviews* • Transcription of the interviews (Walsham 2006); the use of interview outline (though customized for the two different types of participants, i.e., employees or experts); other documents such as the result of the first qualitative phase. • The interviews were analysed iteratively primarily by two authors of the manuscript by refining and enriching the result of the first qualitative phase using open and axial coding techniques. • Given the exploratory nature of the study that aimed for discovery by engaging with "raw" data and the limited scope of the qualitative strand, the notion of theoretical validity is not applicable here.
		Quantitative • Justification of the choice of analysis technique (that are Wilcoxon signed rank test, and generalized van der Waerden test). • A sample size of 1,017 to ensure reasonable power. • The survey was distributed to all participants of the first survey, ensuring that bias in a sampling of subjects is avoided or at least minimized.
Explanation quality	Qualitative inference	The constructs and their relationships identified through the qualitative study were not only plausible and already covered by existing literature (e.g., by the job-demand resources model), but many of them were seen to be relevant to the explanation of the effect of the COVID-19 pandemic on technostress.

	Quantitative inference	• Internal validity concerns were addressed by developing a theoretically robust model, had a reliable data collection process and reliable measurements, and appropriate statistical tests. • Statistical conclusion validity was ascertained by ensuring an appropriate level of significance for tests and analysing the effect sizes. • External validity was ascertained to some degree, given that the original population of the first survey (the basis for the second survey) was representative for the German workforce. However, since we only considered participants who did not change their employer and job between the first and second survey, our results are subject to certain limitations in terms of external validity.
	Integrative inference	• Much of the originality in the study in terms of changes in demands and resources, relevant contextual factors, and their impact on the change in overall technostress and its individual creators can be attributed to the qualitative interviews and the journalistic articles analysed in the qualitative strand. This offered the researchers a real-world view of the effects of the enforced telework, given that the interviewees were employees or experts, and the journalistic articles focused on a broad view on this topic. • Many of the hypotheses developed in the qualitative study were empirically validated as significant and relevant in the quantitative study, although not all hypotheses could be validated. • Although many results were statistically significant and relevant, some cause-effect relationships turned out to be contradictory. For example, it was expected that the characteristics of a contextual variable would influence the change in the overall technostress and its individual technostress creators. However, we could observe that in such cases, the characteristic does not influence the change but keep the intensity of overall technostress and its individual technostress creators on the same level as before the lockdown. In contrast, other characteristics of the contextual factor have then enabled that the intensity has become stronger or weaker compared to the time before the lockdown. • Furthermore, it has also been shown that despite the major changes in demands and resources due to enforced telework, not all technostress creators have changed significantly or at least not to a relevant extent. • Finally, the additional presentation of our results within the four specialist events made the results from the quantitative stand even more comprehensible and thus enriched them • Based on the above, we can say that the synergy between the qualitative interviews followed by a survey, which in turn was followed by four specialist events indicates a satisfactory level of integrative efficiency and integrative efficacy.

Appendix C.5 Effects of the Interaction between Contextual Factors and Time

Contextual Factor	p-Value and Effect Size	Overall Technostress	Techno-Complexity	Techno-Overload	Techno-Insecurity	Techno-Uncertainty	Techno-Invasion
Teleworking Experience (high for n = 168) (H5)	p-value	0.009	0.148	0.227	0.043	0.360	0.024
	V-D A before	0.381	0.447	0.427	0.403	0.379	0.542
	V-D A during	0.434	0.509	0.461	0.444	0.420	0.607
Management Position (given for n = 449) (H6)	p-value	0.012	0.198	0.175	<0.001	0.033	0.030
	V-D A before	0.377	0.456	0.418	0.418	0.387	0.367
	V-D A during	0.442	0.493	0.455	0.487	0.450	0.405
Teleworking Self-Efficacy (high for n = 526) (H7)	p-value	<0.001	<0.001	0.039	<0.001	0.012	0.023
	V-D A before	0.548	0.615	0.550	0.517	0.449	0.366
	V-D A during	0.642	0.690	0.598	0.624	0.532	0.409
Caring Responsibility (given for n = 386) (H8)	p-value	0.911	0.912	0.472	0.687	0.682	0.344
	V-D A before	0.420	0.457	0.450	0.429	0.436	0.421
	V-D A during	0.418	0.461	0.468	0.434	0.441	0.387

Notes: Vargha-Delaney (V-D) A ranges from 0 to 1. It is for the groups that show a corresponding characteristic or where the characteristic is strong. A value of 0.5 indicates the same stress level irrespective of the characteristic. Values < 0.5 (> 0.5) indicate higher (lower) stress levels when the characteristic is given/strong; n = 1,017

Table 41: The Effect of Contextual Factors on the Change in Technostress and Technostress Creators Across Time

Appendix D Analyzing the Effect of Individual Coping Style

Appendix D.1 Rotated Component Matrix

	Factor	
Item	**1**	**2**
Brief COPE 2	0.57	
Brief COPE 3		0.67
Brief COPE 4		0.74
Brief COPE 5	0.58	
Brief COPE 7	0.72	
Brief COPE 8		0.59
Brief COPE 10	0.72	
Brief COPE 11		0.75
Brief COPE 13	**0.49**	**0.48**
Brief COPE 14	0.75	
Brief COPE 15	0.62	
Brief COPE 21	**0.53**	**0.41**
Brief COPE 23	0.67	
Brief COPE 25	0.65	
Brief COPE 26	**0.41**	**0.53**

Notes: Results of a principal axis factoring with varimax rotation. Number of factors was determined through parallel criterium. Factor loadings < .35 are not printed. Cross-loadings are in boldface, these items were excluded for the analysis of the measurement and the structural model

Table 42: Rotated Factor Matrix from Exploratory Factor Analysis

Appendix D.2 Items of the Coping Scales

Subscale	*M*	*SD*	Loading
Active-functional coping			
Brief COPE 7: I've been taking action to try to make the situation better.	0.88	0.84	0.70
Brief COPE 10: I've been getting help and advice from other people.	0.76	0.77	0.76
Brief COPE 14: I've been trying to come up with a strategy about what to do.	0.86	0.84	0.72
Brief COPE 15: I've been getting comfort and understanding from someone.	0.50	0.69	0.70
Brief COPE 23: I've been trying to get advice or help from other people about what to do.	0.63	0.73	0.72
Brief COPE 25: I've been thinking hard about what steps to take.	0.69	0.84	0.68
Dysfunctional coping			
Brief COPE 3: I've been saying to myself "this isn't real".	0.34	0.61	0.69
Brief COPE 4: I've been using alcohol or other drugs to make myself feel better.	0.24	0.54	0.77
Brief COPE 8: I've been refusing to believe that it has happened.	0.34	0.59	0.63
Brief COPE 11: I've been using alcohol or other drugs to help me get through it.	0.22	0.53	0.79

Notes: Items which were excluded during the analysis of the measurement model are omitted. Factor loadings were obtained from confirmatory factor analysis in SEM

Table 43: Items of the Coping Scales: Wording, Descriptive Statistics, and Loadings

Appendix D.3 Moderated Mediation Model

	Productivity			Exhaustion		
Predictor	*Est*	*SE*	*z*[a]	*Est*	*SE*	*z*[a]
Job demands	0.12***	0.04	4.19	0.44***	0.06	14.64
Exhaustion	-0.25***	0.02	-9.22			
Active-functional coping (A)				-0.05*	0.05	-2.25
Dysfunctional coping (D)				0.31***	0.09	8.10
Coping (A) × job demands				-0.05**	0.03	-2.61
Coping (D) × job demands				-0.12***	0.06	-4.85
R^2	0.05			0.36		

Notes: Standardized path coefficients are displayed. [a]Bootstrapped standard errors were used for the interpretation of the results

Table 44: Detailed Results of the Moderated-Mediation Model

Appendix D.4 Conditional Indirect Effects

Moderator values		**Indirect effect**		
A	**D**	***Est***	***SE***	***z*** [a]
Low A (–1 *SD*)	Low D (–1 *SD*)	-0.12***	0.02	-8.22
Medium A (*M*)	Low D (–1 *SD*)	-0.11***	0.02	-8.04
High A (+1 *SD*)	Low D (–1 *SD*)	-0.10***	0.02	-7.58
Low A (–1 *SD*)	Medium D (*M*)	-0.09***	0.02	-6.80
Medium A (*M*)	Medium D (*M*)	-0.09***	0.02	-6.51
High A (+1 *SD*)	Medium D (*M*)	-0.08***	0.02	-5.96
Low A (–1 *SD*)	High D (+1 *SD*)	-0.07***	0.02	-3.93
Medium A (*M*)	High D (+1 *SD*)	-0.06***	0.02	-3.58
High A (+1 *SD*)	High D (+1 *SD*)	-0.05**	0.02	-3.13

Notes: Standardized path coefficients are displayed. [a]Bootstrapped standard errors were used for the interpretation of the results of the indirect effects. * $p < .05$, ** $p < .01$, ***$p < .001$

Table 45: Conditional Indirect Effects from the Moderated-Mediation Model

Appendix E Deriving a Design Theory for Mobile Stress Assessment

To gain practical experience on MSA design by ourselves, we develop five prototypes of MSA systems for different intended applications. During the agile development process and within the studies evaluating our prototypes, we gain important insights that help us understand the interconnectedness of our design theory's components and reveal possible trade-offs that need to be considered in the design process. Each prototype is described in the following structure: it introduces a specific application scenario, outlines the flexible design and development of the prototype, presents the experimental study setting as well as relevant results, and discusses important learnings from this process.

Appendix E.1 Life-integrated Mobile Stress Assessment

Application Scenario: The prototype targets the real-time assessment of perceived stress using only the sensors of a personal smartphone to infer the user's stress level on an interval scale while being best-possibly integrated into their life. Here we provide a brief overview of the system; a detailed description is provided by Gimpel et al. (2015).

Design & Development: We implemented a prototype for the Android platform, tested it with alpha and beta testers within several develop and deploy cycles, and iteratively refined it based on testers' feedback. It reads a total of 36 hardware and software smartphone sensors to identify sensors that might be applicable for stress detection empirically. Exemplary sensors include ambient temperature, audio frequency, and amplitude, an analysis of the user's voice during phone calls, the frequency of pressing the power button, or the number of incoming or outgoing text messages.

Experimental Setup: We applied the prototype within a public field study with 40 participants from countries across the globe and collected a total of 474 stress level observations (average of 11 observations per participant). For calibration purposes within the study and related smartphone sensors to perceived stress, the prototype also asks the user to answer a short questionnaire three times a day. All data is stored on the device but regularly transmitted to a server. Supervised machine learning relating perceived stress to sensor data is conducted offline. Data analysis shows that the smartphone sensor data captured by the prototype suffice to explain the most variance in perceived stress levels (R^2 of 41% using elastic net regression based on 474 answered questionnaires from 40 participants). For more details, see (source disclosed to editors).

Learnings: The prototype's successful development suggests that the design's implementation is generally feasible, even for the most advanced use case. But it also unveils important learnings for the design of MSA. First interviews with alpha testers, for example, revealed issues with high battery consumption and a significant decrease in the battery's charge level. This was the result of a probe interval of sensors being set to only a few seconds. We further learned that a high level of life integration is vital for user acceptance of frequent stress assessment. For model building, the prototype also required to upload the data to cloud storage. The upload interval was chosen as a trade-off between data timeliness and resource usage and upload was limited to times where WiFi is available to spare data connection. Furthermore, very sensitive data (e.g., text messages) stored in first versions were eliminated from the final instantiation due to privacy concerns. Now, the text of an outgoing text message is immediately evaluated using sentiment analysis and discarded directly afterward. Even more important than the choice of sensors and additional services was the appropriate aggregation of sensor data. For each sensor, we used multiple aggregation functions (e.g., minimum and maximum value, average value, and a normalized number of events) to extract valuable information from the data stream. The high R^2 of the stress assessment model involving sensor data gives evidence that the design is suitable for stress assessment. Data analysis further reveals that initializing data processing with a general model built on all users' data can prevent cold-start problems. However, some use cases will use MSA systems over a long period. In these cases, personalization could significantly improve the assessment's performance.

Appendix E.2 Mobile Personalization of Stress Assessment

Application Scenario: We build upon the previous studies and aim to enhance the stress assessment model by applying machine learning techniques for personalization purposes. The basis for this addition is prototype 1, targeting the assessment of perceived stress. Although sensor data collection is also integrated into the user’s life, effective personalization requires to drop the requirement of life integration. This is because model personalization requires regular user feedback on its prediction performance. More details on this study can be found in Gimpel et al. (2019b).

Design & Development: We extend prototype 1 and include a feedback system that enables the user to value the model performance and the actual stress perception level. Like the initial prototype, this has been implemented for the Android platform and further performs data collection, storage, processing, model building, and personalization directly on the smartphone. This brings along a strong limitation of the available resources when compared to cloud or desktop processing. The prototype uses sensory data from the user's environment and behavior to determine perceived stress and continually adapts it to the user via stochastic gradient descent machine learning.

Experimental Setup: The personalization algorithm has been tested with 10 participants; each provided 20 or more observations. Compared to stress prediction with the unpersonalized stress assessment model developed within the evaluation of prototype 1, we could observe a significant improvement of prediction results for all users. However, we found that no fixed learning rate works for all users and some users are more sensitive to small changes in sensor data than others. This supports the claim that stress is highly individual and each user perceives stress differently. Instead, we use the adaptive learning rate algorithm Adadelta (Zeiler 2012) to acknowledge individual differences. Additionally, this episode's lessons further substantiate the findings from previous episodes, e.g., the importance of resource efficiency for user acceptance. Compared to using a desktop computer for calculation purposes, a smartphone has very scarce resources regarding battery capacity, computing power, or simulation tools. This puts high demands on the quality and efficiency of the personalization algorithm. Additionally, this episode also provides interesting implications for MSA systems which apply machine learning techniques. As data arrives over time, the personalization should apply an online learning algorithm that learns one data point at a time, e.g., stochastic gradient descent. Furthermore, as a central requirement of our use case, personalization should integrate passively into the user’s life and abort itself when the assessments are sufficiently good. However, the term “sufficiently good” needs clarification, e.g., in the form of termination criteria that define success and failure of personalization and terminate personalization accordingly (concerning the robustness dimension of requirements). Finally, a general model might be useful to avoid cold start problems. However, the same stress assessment model will probably not stay valid forever and eventually require readjustment to maintain assessment accuracy. Therefore, resumption of the personalization should be considered using criteria that specify cases, in which this readjustment should be triggered.

Appendix E.3 Assessment of Biological Stress using Video Processing

Application Scenario: We built a prototype that continuously assesses an individual's stress level by assessing variations in the user's pupil dilation using video processing techniques. Pupil dilation is a physiological measure, which reflects short-term stress based on biological body reactions (Gao et al. 2007; Mahwah 2010; Winn et al. 1994). This approach can be performed without the need for user's direct interaction or attention and, thus, can be used in everyday life.

Design & Development: We developed a prototype for desktop computers, which uses C++ and the OpenCV (OpenCV 2016c) library. It is capable of assessing variations in pupil dilation without prior calibration or human intervention. Image processing techniques segment the pupil from the iris. The algorithm calculates the pupil/iris ratio of both eyes, averages them to a single value, and evaluates the result of the segmentation to assess cognitive load as stress indicator.

Experimental Setup: The prototype has been applied under controlled conditions in a laboratory study with 23 participants. Of these participants, six participants wore glasses and all eye colors from blue and green to brown were represented. Confounding variables that also influence the pupil dilation, such as room lighting, have been controlled in the experiment. In the experiment, short-term stress is induced by a stress game, which puts participants under stress by inducing different stimuli (Schaaff and Adam 2013). During this, their face is recorded on video. Based on this video stream, the prototype analyzes the pupil diameter changes to detect short-term stress. As a performance measure, physiological stress is assessed using heart rate variability (HRV) as a biological marker. Video, stress game and physiological data have been pre-processed, synchronized with each other and segmented into intervals of one second. Video data that does not meet quality requirements are discarded. Data analysis yields a correlation of 0.471 between pupil dilation and physiological stress as assessed by HRV.

Learnings: We conclude from these results that the assessment of biological stress and the application of video-based sensors are feasible. The development process unveils further important learnings: For biological stress, most physiological markers such as pupil dilation can only be observed with a delay. Simultaneously, physiological markers vary regarding their recovery time, in which the marker returns to the base level. Hence, not every marker might be suitable to detect short-term or long-term stress. Finally, raw data generally is noisy. Especially in uses cases with low fault tolerance, proper pre-processing is critical.

Appendix E.4 Sensor Fusion for Sleep Duration Assessment

Application Scenario: As a contrast to the previous prototypes, we do not target the direct assessment of stress in this episode but build an artificial sleep sensor using sensor fusion techniques as an indicator of stress.

Design & Development: Within an Android prototype, we combine different sensors to assess sleep duration and sleep quality as important indicators of stress. This prototype collects primarily environmental parameters from standard smartphone sensors and does not require the user to change his sleeping routines or habits. The basic idea is that the user does not have to explicitly activate a sleep mode, take a specific sleeping position, or position the smartphone on the bed in a certain way. The prototype is designed to recognize the user’s daily routines over time by combining smartphone sensors. Besides the daytime, which is a rather obvious indicator of sleeping behavior for most people, sleep prediction can benefit from environmental information such as the current location, illuminance, and ambient temperature. Behavioral signs might include the activation of airplane mode or the charging of the smartphone.

Experimental Setup: The prototype has been applied in a field study with nine participants that provided data daily. A total of 30.000 data points has been collected. For model building purposes, data is currently uploaded and processed in the cloud. Different aggregation and methods of data analytics have been tested for model building. Again, the removal of outliers was needed as smartphone sensors generally do not achieve the highest data quality. A random forest model achieved the best accuracy of 93.23%.

Learnings: Again, the learnings regarding resource efficiency were found to be of high importance. But this episode also reveals interesting insights into the processing of data: When multiple sensors (e.g., the WiFi and the radio mast the device is connected to) point to the same real-world feature (in this example the location), it is best to use an aggregation of both values, e.g., the average, to achieve increased robustness. Furthermore, some sensors need some time to calibrate themselves. Thus, the first observations have significantly higher bias and should not be used. In reality, sleeping and waking states do not alter too often. Thus, timely interdependencies between predicted values should be considered in the model.

Appendix E.5 Framework for Data Collection, Storage, and Preprocessing

Application Scenario: Until now, it was an important learning that data collection, storage, and pre-processing are important success factors of stress assessment. Therefore, this prototype aims to build a supportive framework that takes care of data collection, storage, and pre-processing. We used a binary classification model for evaluation purposes, distinguishing the states "stressed" and "not stressed." More details on this study can be found in Beckmann et al. (2017).

Design & Development: The framework works as a module providing the functionality needed to make data collection and merging of different sensors efficient. A Java package and a port to the Android platform are provided as exemplary instantiations and enable the use on both stationary and mobile devices. The instantiation reads various sensors on multiple platforms and saves data on different persistence forms and, thereby, constitutes a linking element between numerous components of the blueprint and can be used as a shortcut to data analytics.

Experimental Setup: We evaluated the framework together with 15 participants, who played the stress-inducing game from prototype 2 with an additional wearable self-tracking device. The framework collects, stores, and pre-processes data from mouse, keyboard, and wearable during the game. To expand the input data, we combined data from different sensors to new, more complex indicators. This approach is commonly referred to as "sensor fusion." Based on this expanded dataset, we trained a binary classification model. The prediction of stress-free states achieves an accuracy of about 99%, whereas stress states can be predicted with an accuracy of approximately 70%.

Learnings: An important learning from this episode is that the application of sensor fusion is a very promising approach and can significantly boost small datasets. We achieved very good results in determining stress on a binary scale. As multiple devices were involved in our experiment, our study demonstrated that sensor fusion is even possible across device boundaries, when the same, standardized data collection framework is used on all devices.

Appendix F Understanding the Misfit in Modern Systems

Appendix F.1 Elaboration of Decision Choice of Mixed-Methods Study

Step	Property	Decision Consideration	Other design decision(s) likely to affect current decision	Design decision and reference to the decision tree
Step1: decide on the appropriateness of mixed-methods research	Research Questions	Qualitative or quantitative method alone was not adequate for addressing the research question. Thus, we used a mixed-methods research approach	None	Identify the research questions • We wrote the qualitative and quantitative research questions separately first and refrain from asking a mixed-methods research question. • The qualitative research questions were: "Which demands from contemporary work practices relating to digital technologies cause stress for employees?" • The quantitative research question was: "How do the different demands relate to each other?"
	Purpose of mixed-methods research	The purpose of our mixed-methods design was to help develop a research model for empirical testing using the results of the qualitative study given the lack of current research on new technostress creators.	Research questions	Developmental purpose and the results from the qualitative strand were used to develop the research model in the quantitative strand.
	Epistemological perspective	The qualitative and quantitative components of the study used different paradigmatic assumptions.	Research questions, purpose of mixed methods	Multiple paradigm stance.
	Paradigmatic assumptions	The researchers believed in the importance of research questions and embraced various methodological approaches from different worldviews.	Research questions, purpose of mixed methods	We used the interpretive and grounded-theory perspective in the qualitative study, then applied a positivist perspective, and deductively tested the developed model in the quantitative study.
Step 2: develop strategies for mixed-methods research designs	Design investigation strategy	The mixed-methods study was aimed to develop and test a theory.	Research questions, paradigmatic assumptions	• Phase 1: exploratory investigation. • Phase 2: confirmatory investigation.
	Strands/phases of research	The study involved multiple phases.	Purpose of mixed methods research	Multistrand design.
	Mixing strategy	The qualitative and quantitative components of the study were mixed at the data-analysis and inferential stages.	Purposes of mixed-methods research, strands/phases of research	Partially mixed methods.
	Time orientation	We started with the qualitative phase, followed by the quantitative phase.	Research questions, strands/phases of research	Sequential (exploratory) design.
	Priority of methodological approach	The qualitative and quantitative components are equally important.	Research questions, strands/phases of research	Equally dominant design with the qualitative and quantitative study being equally important.
Step 3: develop strategies for collecting and analyzing mixed-methods data	Sampling design strategies	The samples for the quantitative and qualitative components of the study differed, but they came from the same underlying population (parallel samples).	Design investigation strategy, time orientation	Purposive sampling for the qualitative study given interdisciplinary nature of technostress in the working context, probability sampling for the quantitative study.
	Data collection strategies	• Qualitative data collection in phase 1. • Quantitative data collection in phase 2.	Sampling design strategies, time orientation, strands/phases of research	• Qualitative study: open-ended questioning using a pre-designed interview guideline. • Quantitative study: closed-ended questioning (i.e., traditional survey design).
	Data analysis strategy		Time orientation, data collection strategy, strands/phases of research	Sequential qualitative-quantitative analysis.

Appendix F.2 Mixed-Method Approach and Criteria

Quality Aspects	Quality Criteria	Response to Venkatesh et al. 's (2013) guideline
Purpose of mixed method approach	"Development"	This study is divided into two phases: (1) after an extensive literature search, a qualitative study involves 15 interviews with experts on different fields including employee and employer representatives, experts from occupational health management, ethics, ergonomics, informatics, and human resource management followed by seven focus group interviews with employees to understand current factors that could result in technostress (2) multiple large quantitative surveys ($n_{pre\text{-}test}$ = 455, n_1 = 1,560, n_2 = 3,00) to test for the identified factors and their underlying structure. The qualitative study was used to identify the factors for theory building and survey development, which was subsequently tested in the quantitative study.
	Sequential dominant qualitative followed by a less-dominant quantitative investigation	The scope and objectives of the quantitative investigation using statistical techniques are to support the qualitative investigation and to inspect a potential hierarchical structure.
Design quality	Design adequacy	The study used 15 qualitative interviews with experts from different fields along with an in-depth-analysis of the transcribed data followed by a seven qualitative focus group discussion. After this qualitative phase, a quantitative survey was designed und distributed. This strategy of examining "raw" data from the phenomenon as a "prelude" to the larger quantitative study ensured that the research model tested using the quantitative study was relevant to the phenomenon of interest. In doing so, it sought to combine the advantages of the two approaches, achieving depth and insight into the phenomenon as well as the breadth of coverage.
		Qualitative – Expert Interviews • Selecting suitable interviewees: The interviewees were experts on fields that related to technostress and address this topic from a variety of different perspectives and were thus in sum seen as suitable. • Entering the field with credibility: The interviews were primarily conducted by authors of the manuscript, who were (at the time of the study) working on his/her Ph.D. thesis (thus seen in high respect in society). • Conduct of interviews: All interviews were conducted using a pre-designed interview guideline. *Qualitative – Focus Group Discussion* • Selecting suitable interviewees: The interviewees were groups of white-collar-workers of different companies using digital technologies to perform their work tasks or researchers on the field of digital technology use and were thus seen as suitable. • Entering the field with credibility: The interviews were primarily conducted by authors of the manuscript, who were (at the time of the study) working on his/her Ph.D. thesis (thus seen in high respect in society). • Conduct of interviews: All interviews were conducted using a pre-designed interview guideline.
	Analytical adequacy	*Qualitative (Expert Interviews and Focus Group Discussion)* • Transcription of all interviews and photo-logging of all focus group discussions; the use of interview outline (though customized for the two different types of interviews) • Each interview was analyzed by at least one author by using detailed analysis techniques and the principle of theoretical engagement (Sarker et al. 2013a) and overall multiple authors participated in the analysis. • Labeling and relabeling of the relevant concepts by more than half of the authors after the generation of the codes. The process was iterative and roughly resembled a constant comparative analysis, ending when theoretical saturation occurred (Glaser and Strauss 2017). • While no notion of interrater reliability was used, the identification and selection of the concepts represented a consensus among a great number of researchers involved in data collection and analysis, implying some form of convergence and/or reliability.
		Qualitative • Justification of the choice of analysis technique (that is, factor analysis, structural equation modeling). • A pre-test sample (n = 455), a developmental sample (n = 1,560) and a validation sample (n=3,000) to ensure reasonable power. • The survey was randomly distributed und is representative of the German workforce ensuring that bias in a sampling of subjects is avoided or at least minimized.

Explanation quality	Qualitative inference	The constructs identified through the qualitative study were not only plausible, but many of them were seen to be relevant in the literature.
	Quantitative inference	• Internal validity concerns were addressed by developing a model that was theoretically robust, had a reliable data collection process and reliable measurements, and appropriate statistical tests. • Statistical conclusion validity, considered to be a "special case of internal validity," was ascertained by ensuring construct validity, and appropriate level of significance for tests, and testing for common method bias. • External validity was ascertained to some degree given that the sample is representative of the German workforce. In this sense, the results will likely be similar if studied in an external setting.
	Integrative inference	• Much of the originality in the study in terms of current and new demands from digital work, their impacts on the negative psychological responses, and in turn on job satisfaction and productivity can be attributed to the qualitative interviews that was conducted in the introductory phase • Many of the constructs that were identified in the qualitative study were empirically validated as significant in the quantitative study. • An additional second-order analysis has brought further understanding of possible relationships between existing and new demands from digital work. Four second-order factors were considered. • Model comparisons about the structure of the twelve first-order and the four second-order factors were performed. The fit measures for the correlated group factor model were slightly better than for the second-order model. • Based on the above, we can say that we have been able to achieve a reasonable degree of balance between comprehensiveness and parsimony in the model, and hence integrative efficacy. The synergy between the qualitative interviews followed by a survey, the results of which could be understood in light of the qualitative study indicates a satisfactory level of integrative efficiency and integrative efficacy.

Appendix F.3 Development and Validation of Measures

For the development and validation of measures, we followed two different processes depending on the prerequisites. If possible, the use of existing measures is recommended (Urbach and Ahlemann 2010). In the case of new constructs without existing measures, we followed the guidelines formulated by Hinkin (1998) and MacKenzie and Podsakoff (2011). Therefore, the following passages are structured according to the steps recommended by MacKenzie and Podsakoff (2011).

Step 1: *Develop a conceptual definition of the construct*

The first step is to define the constructs conceptually and to discuss "how the construct differs from other related constructs" MacKenzie and Podsakoff (2011, p. 298). This step has been covered in Phase 1 of our mixed-methods study. The qualitative investigations concluded with a definition of twelve demands from digital work, as presented in Table 22 within the research article.

Step 2: *Generate items to represent the construct*

For existing scales, we collected the items from Ragu-Nathan et al. (2008) (i.e., invasion, overload, complexity, insecurity, and uncertainty), Ayyagari et al. (2011) (i.e., unreliability, role ambiguity, and invasion of privacy), and Galluch et al. (2015) (i.e., interruptions). The items were slightly adapted. For example, instead of the wording "technology" or "ICT", we consistently used the term "digital technology and media". The items were collected in English and then translated in a four-step approach based on Beaton et al. (2002) into German since the survey's final sample consisted of German employees. Therefore, two bilingual speakers translated the questions in parallel. They met afterward to discuss discrepancies with a third bilingual speaker and agree on the most suitable translation. A fourth bilingual speaker back-translated the items into English again and check the validity.

For the newly identified demands, non-availability, performance control, and lacking sense of achievement, we developed items based on the definitions of these constructs (Table 22) considering standard guidelines (Hinkin 1998; MacKenzie and Podsakoff 2011; Podsakoff et al. 2003). We created the items to be short, simple, and precise and used appropriate language for employees (Hinkin 1998; MacKenzie and Podsakoff 2011). During the development, we carefully made sure that the items only address a single aspect (i.e., no connection of different statements in one item) to prevent the respondent's confusion (Hinkin 1998). High quality of items and careful construction of the statements used are necessary procedural remedies to avoid common method bias (CMB) (Podsakoff et al. 2003). Since it is likely in a scale development process that approximately half of the items may be dropped due to reliability and validity issues (Hinkin 1998), we generated six items for each creator of digital stress so that at least three items would remain after the validation process. Because the questionnaire was rather long, reverse coded items were included to reduce response patterns in the first draft of the survey. The items of the three new scales were generated in German. We translated the final versions of the items into English for further reusability according to the same procedure as we translated the existing English item scales into German.

We used a five-point Likert-type rating scale from 0 = "*I do not agree at all*" to 4 = "*I totally agree*" to measure all twelve demands.

Step 3: *Assess the content validity of the items*

To evaluate the newly developed item scales' content and face validity, we conducted a card-sorting experiment via an online matching task with fellow researchers (Moore and Benbasat 1991; Thatcher et al. 2018). Thirty-nine participants completed the task. Items that were correctly matched by less than 85 % of participants were subject to refinement. Thus, we changed the wording of these items to fit the corresponding demands from digital work better and finished this step of item generation with the revised scales.

Step 4: *Formally specify the measurement model*

We specify the measurement model as first-order reflective for each of the established scales as suggested by Ragu-Nathan et al. (2008, p. 428), who "[…] have conceptualized technostress creators […] as reflective or superordinate (Edwards 2001, Law and Wong 1999) constructs. This implies that (1) each of the first order constructs represents a facet or manifestation and can be viewed as one of its dimensions and the direction of causality is from the second order construct to its facets, the first order constructs, (2) the first order constructs are interchangeable, (3) covariation among the first order constructs is not unexpected, and (4) the nomological networks associated with them are expected to be similar (Jarvis et al. 2003)". For the newly developed scales we follow the suggestion from Ragu-Nathan et al. (2008, p. 428) and are "consistent with previous literature on stress that models stress as a reflective construct (Law et al. 1998)". Furthermore, we allow for correlation among the twelve demands. In a later step, we will investigate whether there are higher-order structures among the twelve demands.

Step 5: *Collect data to conduct pre-test*

Next, we collected data for evaluating our measures' factor structure and validity (Hinkin 1998; MacKenzie and Podsakoff 2011). First, we acquired respondents for a pre-test via an external research panel focusing on the German workforce. Respondents were paid 3,10 € for participation in the study. Four hundred forty-five respondents took part in the study providing data in sufficiently good quality (e.g., consistency checks between individual items, meaningful answers to free-text questions).

Step 6: *Scale purification and refinement*

On the pre-test dataset, we performed an EFA to assess the quality of our questionnaire carefully and did a preliminary analysis of all scales (Hinkin 1998). Parallel analysis (Horn 1965) suggested to extract nine factors but also showed a strong first factor, which suggests that a minimum average partial (MAP) test (Beauducel 2001) is more adequate to determine the number of factors to extract (Velicer 1976). The MAP test suggested 13 factors.

We used principle axis factoring and oblique rotation to identify the factors. As can be seen in Table 46, the items for overload as well as for interruptions loaded on one joint factor. Further, the items for non-availability and for lacking sense of achievement loaded on two separate factors each. These "sub-factors" were compounded of items that were formulated in the same direction. Thus, we decided to reformulate all reversely coded items. Furthermore, we removed the first item of invasion of privacy due to its cross-loading on performance control. As both, the overload and interruptions scales were validated in prior research (even if not used jointly), we for now refrained from adaptations.

Item	F01	F02	F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13
INV01	0.753												
INV02	0.667												
INV03	0.483												
OVE01		0.367											
OVE02		0.529											
OVE03		0.526											
OVE04		0.565											
COM01			0.582										
COM02			0.817										
COM03			0.627										
COM04			0.688										
COM05			0.805										
INS01				0.309									
INS02				0.419									
INS03				0.420									
INS04				0.387									
UNC01					0.650								
UNC02					0.719								
UNC03					0.860								
UNC04					0.917								
UNR01						0.886							
UNR02						0.943							
UNR03						0.764							
ROL01							0.564						
ROL02							0.675						
ROL03							0.781						
ROL04							0.525						
IOP01								0.416	0.439				
IOP02								0.877					
IOP03								0.892					
IOP04								0.834					
INT01		0.318											
INT02		0.330											
INT03		0.328											
PER01									0.571				
PER02									0.668				
PER03									0.798				
PER04									0.702				
PER05									0.758				
PER06									0.675				
NON01										0.901			
NON02										0.909			
NON03											0.676		
NON04											0.778		
NON05											0.766		
NON06										0.476			
LSA01												0.761	
LSA02												0.852	
LSA03												0.850	
LSA04													0.832
LSA05												0.782	
LSA06													0.866

Notes: Loadings smaller than 0.4 are not shown; INV = Invasion, OVE = Overload, COM = Complexity, INS = Insecurity, UNC = Uncertainty, UNR = Unreliability, ROL = Role Ambiguity, IOP = Invasion of Privacy, INT = Interruptions, PER = Performance Control, NON = Non-Availability, LSA = Lacking Sense of Achievement

Table 46: Item loadings from EFA on the Pre-Test Sample (n = 445)

Step 7: *Gather data from new sample and reexamine scale properties*

Using the revised scales, we collect new data from 1,560 respondents (Table 47) participating in an online survey (developmental sample) through the same external research panel as in the pre-test.

Gender	***N***	%	**Employment**	**N**	**%**
Male	834	53	Full-time (>20 h)	1488	95
Female	726	47	Half-time (<20 h)	72	5

Age (M = 43.19)	**N**	**%**	**Technology Use**	**N**	**%**
<25	53	3	Never	0	0
25-34	341	22	Seldom	0	0
35-44	427	27	Weekly	80	5
45-54	406	26	Daily	203	13
55-64	328	21	Several Times	1277	82
>65	5	<1			

Education	**N**	**%**
No Diploma	0	0
Primary School Education	23	1
Secondary School Education	205	13
Tertiary Education / High School Diploma	170	11
Completed Apprenticeship	485	31
College Degree (Bachelor)	286	18
College Degree (Master)	346	22
Dissertation (PhD)	45	3

Table 47: Demographic Properties of the Developmental Sample (n_1 = 1,560)

Using the revised scales, we conducted a confirmatory factor analysis (CFA) to measure the models' fit according to standard fit measures likes the root mean square error of approximation (RMSEA) and the square root mean residual (SRMR) for global measures, the comparative fit index (CFI), Tucker-Lewis index (TLI), and the Normed Fit Index (NFI) for incremental measures, and the Adjusted Goodness of Fit Index (AGFI) for the assessment of the parsimony. We applied the thresholds suggested by Lei and Wu (2007) and Gefen et al. (2000). We do not report χ^2 or χ^2/df as these are not considered meaningful for samples of our size. Results are displayed in Table 48.

Fit measures		Threshold	Source of Threshold	Demands from Digital Work
Global measures	RMSEA	< 0.06	Lei and Wu (2007)	0.050
	SRMR	< 0.05	Gefen et al. (2000)	0.049
Incremental measures	NFI	> 0.90	Gefen et al. (2000)	0.920
	TLI	> 0.90	Gefen et al. (2000)	0.929
	CFI	> 0.90	Gefen et al. (2000)	0.935
Parsimony	AGFI	> 0.80	Gefen et al. (2000)	0.826

Table 48: Fit Measures from a CFA on the Developmental Sample (n_1 = 1,560)

The data from the developmental sample showed a good fit. Furthermore, we evaluated reliability using Cronbach's Alpha and convergent validity using the item loadings and average variance extracted (AVE) from the confirmatory factor analysis. The descriptive statistics, loadings, Cronbach's Alpha values, and AVE are presented in Table 49. Cronbach's Alpha showed values of at least 0.82 for all scales indicating internal consistency. Almost all loadings of the items on their respective latent factors in the CFA were above the value of 0.70, which indicates that the underlying construct explains more than 50 % of the variance of this item. Also, the AVE (i.e., assessing whether, on average, over all items, the underlying latent construct explains more than 50 % of the variation in its indicators in sum) of all constructs was above 0.50. Thus, convergent validity was satisfactory.

Construct	Items	*M*	*SD*	Loadings	α	AVE
Invasion	3	1.14	1.33	0.64-0.89	0.82	0.60
Overload	4	1.52	1.31	0.71-0.85	0.88	0.66
Complexity	5	1.21	1.21	0.76-0.87	0.91	0.67
Insecurity	4	1.18	1.26	0.69-0.84	0.83	0.57
Uncertainty	4	1.69	1.24	0.76-0.86	0.88	0.65
Unreliability	3	1.75	1.22	0.85-0.94	0.92	0.79
Role Ambiguity	4	1.22	1.23	0.79-0.89	0.91	0.72
Invasion of Privacy	3	1.95	1.38	0.90-0.94	0.93	0.85
Interruptions	3	1.49	1.26	0.85-0.90	0.91	0.76
Performance Control	6	1.95	1.36	0.77-0.88	0.92	0.67
Non-Availability	6	1.19	1.27	0.79-0.88	0.93	0.68
Lacking Sense of Achievement	6	1.04	1.22	0.79-0.94	0.96	0.81

Table 49: Descriptive Statistics, Internal Consistency, AVE, and Factor Loadings on the Developmental Sample (n_1 = 1,560)

Step 8: *Assess Scale Validity*

Additionally, we assessed the discriminant validity of our twelve constructs amongst themselves based on the Fornell-Larcker criterion (Fornell and Larcker 1981) as Cronbach's Alpha does not account for the dimensionality of constructs. The Fornell-Larcker criterion compares the size of the intercorrelations of the latent constructs to the AVE. The square root of the AVE printed in the diagonal of Table 50 was higher than the intercorrelations of each construct with the other latent factors. Therefore, we considered construct validity as given.

Construct	INV	OVE	COM	INS	UNC	UNR	ROL	IOP	INT	PER	NON	LSA
INV	**0.78**											
OVE	0.65	**0.82**										
COM	0.63	0.66	**0.82**									
INS	0.73	0.72	0.66	**0.76**								
UNC	0.48	0.56	0.43	0.64	**0.81**							
UNR	0.48	0.62	0.51	0.51	0.43	**0.89**						
ROL	0.65	0.69	0.75	0.68	0.44	0.58	**0.85**					
IOP	0.42	0.49	0.43	0.41	0.27	0.44	0.54	**0.92**				
INT	0.57	0.71	0.61	0.57	0.42	0.62	0.70	0.54	**0.87**			
PER	0.40	0.59	0.45	0.50	0.38	0.45	0.55	0.67	0.55	**0.82**		
NON	0.59	0.54	0.59	0.55	0.34	0.52	0.66	0.44	0.58	0.42	**0.82**	
LSA	0.64	0.62	0.67	0.64	0.41	0.48	0.75	0.47	0.65	0.43	0.64	**0.90**

Notes: Diagonal elements are square root AVE; off-diagonal elements are correlations; INV = Invasion, OVE = Overload, COM = Complexity, INS = Insecurity, UNC = Uncertainty, UNR = Unreliability, ROL = Role Ambiguity, IOP = Invasion of Privacy, INT = Interruptions, PER = Performance Control, NON = Non-Availability, LSA = Lacking Sense of Achievement

Table 50: Discriminant Validity on the Developmental Sample (n_1 = 1,560)

The accomplished analyses show that the scales to assess the digital work demands perform well, and there is evidence for twelve underlying factors in the data. The translated scales worked well, just as did the three scales for the newly developed constructs from scratch. Especially as we initially intended to potentially reduce the number of items for non-availability, performance control, and lacking sense of achievement. However, all newly generated items' psychometric properties were good enough for retaining them in the final scales. The final scales from this process is presented in Appendix F.4.

MacKenzie and Podsakoff (2011) also mentions in step 8 that it should also be examined to what extent a multidimensional structure is present, as we already pointed out in our fourth step.

We defer steps 8 and 9 to the sub-sections in the main part of this chapter where we first use the developmental sample (n_1 = 1,560) to investigate the structure of the twelve demands. Next, we gather new data for the validation sample (n_2 = 3,000) to re-assess scale validity, select among the potential structures of the demands, and embed the final structure in a nomological net. We omit step 10, as it is not relevant for our research questions.

Appendix F.4 Final Scale

Construct	Item
Invasion (Adapted from Tarafdar et al. 2007)	INV01: I have to sacrifice my vacation and weekend time to keep current on digital technologies.
	INV02: I have to be in touch with my work even during my vacation due to digital technologies.
	INV03: I feel my personal life is being invaded by digital technologies.
Overload (Adapted from Tarafdar et al. 2007)	OVE01: I am forced by digital technologies to do more work than I can handle.
	OVE02: I am forced to work with very tight time schedules by digital technologies.
	OVE03: I am forced to change my work habits to adapt to new technologies.
	OVE04: I have a higher workload because of increased technology complexity.
Complexity (Adapted from Tarafdar et al. 2007)	COM01: I do not know enough about digital technologies to handle my job satisfactorily.
	COM02: I need a long time to understand and use new technologies.
	COM03: I do not find enough time to study and upgrade my technology skills.
	COM04: I find new recruits to this organization know more about computer technologies than I do.
	COM04: I often find it too complex for me to understand and use new technologies.
Insecurity (Adapted from Tarafdar et al. 2007)	INS01: I feel constant threat to my job security due to new digital technologies.
	INS02: I have to constantly update my skills with regard to digital technologies to avoid being replaced.
	INS03: I am threatened by coworkers with newer technology skills.
	INS04: I feel there is less sharing of knowledge about digital technologies among coworkers.
Uncertainty (Adapted from Tarafdar et al. 2007)	UNC01: There are constant changes in computer software in our organization.
	UNC02: There are constant changes in computer hardware in our organization.
	UNC03: There are frequent upgrades in computer networks in our organization.
	UNC04: There are always new developments in the technologies we use in our organization.
Unreliability (Adapted from Ayyagari et al. 2011)	UNR01: I often experience that features provided by digital technologies are not dependable.
	UNR02: I often experience that the capabilities provided by digital technologies are not reliable.
	UNR03: I often experience that digital technologies do not behave in a highly consistent way.
Role Ambiguity (Adapted from Ayyagari et al. 2011)	ROL01: I am not sure whether I have to deal with problems with digital technologies or with my work activities.
	ROL02: I am not sure what to prioritize: problems with digital technologies or my work activities.
	ROL03: I cannot allocate time properly for my work activities because the time spent on solving problems with digital technologies varies.
	ROL04: Time spent resolving digital techonlogy problems takes time away from fulfilling my work responsibilities.
Invasion of Privacy (Adapted from Ayyagari et al. 2011)	IOP02: I feel my privacy can be compromised because my activities using digital technologies can be traced.
	IOP03: I feel my employer could violate my privacy by tracking my activities using digital technologies.
	IOP04: I feel that my use of digital technologies makes it easier to invade my privacy.

Interruptions (Adapted from Galluch et al. 2015)	INT01: I received too many interruptions during the task through digital technologies.
	INT02: I experienced many distractions during the task due to digital technologies.
	INT03: The interruptions caused by digital technologies are frequent.
Performance Control (Self-developed)	PER01: I feel that my professional performance is monitored using digital technologies.
	PER02: I feel that professional achievements can be better monitored because of digital technologies.
	PER03: Due to digital technologies other people can easily monitor my performance.
	PER04: I feel that my professional achievements can be compared with the achievements of my <colleagues/competitors> due to digital technologies.
	PER05: My performance can be continually assessed through digital technologies.
	PER06: I have the feeling that more of the mistakes I make during work can be discovered through digital technologies.
Non-Availa-bility (Self-de-veloped)	NON01: I do not have the necessary digital technologies at hand that I need to carry out my activities.
	NON02: The digital technologies available to me are not sufficient to execute my work tasks.
	NON03: I could do better work if I had more digital technologies available.
	NON04: I am restricted in the execution of my work tasks because I am lacking essential technologies.
	NON05: I could handle my work tasks better if I had more rights to the relevant digital tech-nologies.
	NON06: I do not have the right to use the digital technologies which I need to do my job.
Lacking Sense of Achieve-ment (Self-de-veloped)	LSA01: I feel that I do not know what I have accomplished at the end of a working day when using digital technologies.
	LSA02: When working with digital technologies, I lack the feeling of knowing what I have personally achieved.
	LSA03: It is hard for me to recognize the results of my work while using digital technologies.
	LSA04: I can’t tell what progress I’ve made at the end of the day when working with digital technologies.
	LSA05: It is very difficult for me to recognize my work success and I have to think carefully about what I have actually achieved when using digital technologies.
	LSA06: Digital technologies do not help me to assess the progress I made at work.

Notes: This scale may not be used commercially

Table 51: Final Scale for the Demand from Digital Work

Appendix F.5 Item loadings for the Bi-Factor Model

Items	Bi-Factor	COM	INS	INT	INV	IOP	NON	LSA	OVE	PER	ROL	UNC	UNR
COM01	0.60	0.46											
COM02	0.63	0.60											
COM03	0.66	0.45											
COM04	0.60	0.51											
COM05	0.63	0.61											
INS01	0.59												
INS02	0.58		0.51										
INS03	0.64		0.54										
INS04	0.59												
INT01	0.70			0.49									
INT02	0.67			0.51									
INT03	0.71			0.56									
INV01	0.56				0.64								
INV02	0.63				0.59								
INV03	0.57												
IOP02	0.59					0.67							
IOP03	0.57					0.74							
IOP04	0.57					0.66							
NON01	0.63						0.50						
NON02	0.64						0.47						
NON03	0.50						0.67						
NON04	0.61						0.65						
NON05	0.61						0.56						
NON06	0.65						0.47						
LSA01	0.84												
LSA02	0.84							0.46					
LSA03	0.84							0.51					
LSA04	0.84							0.49					
LSA05	0.84							0.47					
LSA06	0.72												
OVE01	0.74								0.41				
OVE02	0.71								0.46				
OVE03	0.58												
OVE04	0.71								0.46				
PER01	0.64									0.46			
PER02	0.47									0.62			
PER03	0.51									0.71			
PER04	0.63									0.56			
PER05	0.54									0.67			
PER06	0.57									0.51			
ROL01	0.74										0.42		
ROL02	0.76										0.49		
ROL03	0.76												
ROL04	0.60												
UNC01	0.46											0.61	
UNC02	0.51											0.59	
UNC03	0.44											0.69	
UNC04	0.48											0.71	
UNR01	0.55												0.64
UNR02	0.61												0.72
UNR03	0.64												0.59

Notes: Loadings smaller than 0.4 are not shown; INV = Invasion, OVE = Overload, COM = Com-plexity, INS = Insecu-rity, UNC = Uncertainty, UNR = Unreliability, ROL = Role Ambiguity, IOP = Invasion of Privacy, INT = Interruptions, PER = Performance Control, NON = Non-Availability, LSA = Lacking Sense of Achievement

Table 52: Bi-Factor Model Item loadings on the Developmental Sample (n_1 = 1,560)

Appendix F.6 Psychometric Properties of the Final Scale

Construct	Items	*M*	*SD*	Loadings	α	AVE
Invasion	3	1.15	1.32	0.40-0.86	0.82	0.60
Overload	4	1.54	1.31	0.55-0.71	0.89	0.67
Complexity	5	1.16	1.22	0.55-0.87	0.91	0.66
Insecurity	4	1.16	1.27	0.45-0.79	0.83	0.57
Uncertainty	4	1.70	1.25	0.72-0.83	0.88	0.64
Unreliability	3	1.75	1.21	0.78-0.94	0.92	0.78
Role Ambiguity	4	1.20	1.24	0.40-0.61	0.91	0.70
Invasion of Privacy	3	1.81	1.39	0.85-0.98	0.94	0.84
Interruptions	3	1.48	1.27	0.74-0.83	0.90	0.76
Performance Control	6	1.90	1.38	0.65-0.89	0.93	0.69
Non-Availability	6	1.18	1.27	0.66-0.91	0.93	0.70
Lacking Sense of Achievement	6	1.02	1.27	0.70-0.94	0.96	0.80

Table 53: Descriptive Statistics, Internal Consistency, AVE, and Factor Loadings on the Validation Sample (n_2 = 3,000)

We conducted Harman's single factor test to derive whether CMB seems a problem in our data. All items were subject to principal components analysis (Podsakoff et al. 2003). More than one factor was extracted, the largest one accounting for about 13% of the variance, so CMB is considered as uncritical. Second, we employed the correlational marker technique as a post hoc test (Lindell and Whitney 2001; Richardson et al. 2009). Therefore, we partialled out the smallest and the second-smallest shared variance in bivariate correlations among substantive exogenous latent variables (i.e., demands from digital work). Since we found only minor changes in significance of the bivariate correlation among these variables, we assume that CMB is not a concern in this study.

Construct	INV	OVE	COM	INS	UNC	UNR	ROL	IOP	INT	PER	NON	LSA
INV	**0.78**											
OVE	0.65	**0.82**										
COM	0.63	0.66	**0.81**									
INS	0.73	0.72	0.66	**0.76**								
UNC	0.48	0.56	0.43	0.64	**0.80**							
UNR	0.48	0.62	0.51	0.51	0.43	**0.89**						
ROL	0.65	0.72	0.76	0.68	0.45	0.58	**0.84**					
IOP	0.42	0.49	0.43	0.41	0.27	0.44	0.51	**0.92**				
INT	0.57	0.71	0.61	0.57	0.42	0.62	0.74	0.54	**0.87**			
PER	0.40	0.59	0.45	0.50	0.38	0.45	0.57	0.67	0.55	**0.83**		
NON	0.59	0.54	0.59	0.55	0.34	0.52	0.67	0.44	0.58	0.42	**0.84**	
LSA	0.64	0.62	0.67	0.64	0.41	0.48	0.75	0.47	0.65	0.43	0.64	**0.90**

Notes: Diagonal elements are square root AVE; off-diagonal elements are correlations; INV = Invasion, OVE = Overload, COM = Complexity, INS = Insecurity, UNC = Uncertainty, UNR = Unreliability, ROL = Role Ambiguity, IOP = Invasion of Privacy, INT = Interruptions, PER = Performance Control, NON = Non-Availability, LSA = Lacking Sense of Achievement

Table 54: Discriminant Validity According to Fornell-Larcker on the Validation Sample (n_2 = 3,000)

Appendix F.7 Results of the Nomological Network

Outcome / Digital Demand	Job-Satisfaction			Productivity		
	Est	z	p	Est	z	p
Control: Age	0.139	7.386	0.000	0.164	8.456	0.000
Control: Gender	-0.011	-0.612	0.540	0.006	0.293	0.770
Control: Technology Use	-0.024	-1.291	0.197	0.023	1.194	0.233
Impediment	-0.390	-4.774	0.000	-0.673	-7.590	0.000
Inference	-0.095	-0.919	0.358	0.464	4.198	0.000
Constant Change	0.427	6.907	0.000	0.253	4.456	0.000
Exposure	-0.102	-2.309	0.021	0.164	8.456	0.000

Table 55: Results of the Nomological Network on the Validation Sample (n_2 = 3,000)