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The role of agent autonomy in using decision support systems at work

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ABSTRACT

Digitalization of work leads to ever-increasing information processing requirements for employees. Agent-based decision support systems (DSS) can assist employees in information processing tasks and decrease processing requirements. With increasing system capabilities, agency between the user and the system shifts, with high autonomy DSS being able to take over complete information processing tasks. In the present study, we distinguish degrees of DSS autonomy, operationalized by levels of automation (LOA), the delegation of task processing stages, and user control. In two vignette studies, we investigate the effects of DSS autonomy on perceptions of information load reduction, technostress, and user intention as well as the moderating role of technology and job experience. With high DSS autonomy, participants reported higher levels of information load reduction and technostress as well as lower levels of user intention. Job experience was a significant moderator. For high autonomy DSS, participants in the high job experience condition indicated greater information load reducation, lower technostress, and higher user intentions. Results suggest, that while being beneficial for decreasing information load, high DSS autonomy may negatively impact technostress and user intentions. It is suggested that technology and job training may improve user reactions.

1. Introduction

Digital systems (e.g. intelligent agent-assisted decision support systems, DSS) are increasingly implemented at work to assist employees with decision making, to decrease information load, or to increase efficiency (Howard, 2019; Larson & DeChurch, 2020; Sheridan, 2019). DSS are varied in their capabilities and applications and can range from simple systems, such as email spam filters, to complex DSS for cancer detection (e.g. Tan et al., 2016). With the advancement of artificial intelligence, DSS are becoming increasingly autonomous, being able to take over diverse and complex tasks. Despite potential benefits for individuals' information processing requirements, the implementation of DSS at work still leads to problems, as employees struggle to adapt (Cascio & Montealegre, 2016; Mitchell & Brynjolfsson, 2017). Employees' reactions towards these technologies as well as work outcomes may be positively or negatively impacted by DSS use (e.g. Day et al., 2010). For example, highly autonomous DSS can process large amounts of information, decreasing employees' information load (Eppler & Mengis, 2004). At the same time, when delegating many task processing stages to a system, employees' tasks and roles change, increasing the need for monitoring, which has been associated with increased demands (Day et al., 2012; Endsley, 2017; Hancock, 2013). Research in the field of work and organizational psychology highlights, that a lack of control over task processing can pose as s technology demand. These demands are determining factors for employees' technology-related reactions, such as information overload or stress (Day et al., 2012). At the same time, research in the field of human computer interaction (HCI) shows that highly autonomous systems can trigger skepticism, low technology acceptance, or low trust amongst users, which can decrease intention to use the system (Flemisch et al., 2012; Lee & See, 2004). With an increase in system autonomy, there is a shift in agency over task processing, from the employee to the technology, which will fundamentally transform today's work environments (Parker & Grote, 2020). Although, research findings relate a system's level of automation to autonomy (also see Level of Automation, LOA or degree of automation, DOA; e.g. Endsley, 2017; Onnasch et al., 2014) and consequently to user reactions that directly relate to task processing (e.g. situation awareness), this does not fully address the shift of agency in task processing that takes place when users collaborate with DSS. Thus far, it is still unclear how full, partial, and low degrees of agent autonomy impact users' individual experiences

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while using DSS. In this paper, we aim to investigate how autonomy affects user reactions in the work context. Specifically, we investigate the relationship between different levels of autonomy and cognitive (information overload), affective (technostress), and behavioral reactions (user intentions) towards these systems.

Central theories of HCI research emphasize that user interaction with autonomous systems is not only impacted by system characteristics, such as the system's reliability, but also by individual factors (e.g., Endsley, 2017). It is thus suggested that individuals do not react equally to DSS (Venkatesh et al., 2016). For instance, Eppler and Mengis (2004) describe that individuals differ in how much they are influenced by large information loads and whether they experience information overload. Individual differences, such as the level of technology or job-related experience, have been shown to affect initial reactions to autonomous technologies (Goddard et al., 2012; Manzey et al., 2009; Ragu-Nathan et al., 2008; Sheridan, 2019; Ulfert & Scherer, 2020). For example, DSS with diverse task processing capabilities (i.e. processing multiple task types) will also increase system complexity, requiring increasingly skilled users to understand the functioning of the system and maintain situation awareness (see e.g., Ironies of Automation; Bainbridge, 1983). However, systematic comparisons of how individual users react to DSS with varying autonomy levels are still lacking.

The present study adds to current literature on interacting with intelligent DSS at work by (1) systematically studying the effects of DSS autonomy on cognitive (information overload), affective (technostress), and behavioral user reactions (user intention) towards these systems and (2) by exploring the effects of individual differences (i.e. experience) on user outcomes and specifically the moderating role of technology and job experience. This allows combining psychological models of occupational stress (Bakker & Demerouti, 2007) with HCI frameworks to gain a deeper understanding of how employees interact with DSS at work.

1.1. Autonomy in agent-assisted decision support systems

DSS are generally "dedicated to improving the performance of knowledge workers in organizations through the application of information technology." (Sprague & Watson, 1986, p. 4) by providing information, relevant to the individual worker or team. Today, by utilizing methods of artificial intelligence (e.g. agents), DSS are becoming increasingly competent and autonomous, being able to act instead of a user and to improve their performance over time (Gao & Xu, 2009; Wooldridge & Jennings, 1995). Depending on the agent's architecture, DSS can range from low autonomy regarding the information processing task (e.g., highlighting important information), to highly autonomous DSS that take over complete tasks without the user having an impact on task processing (Russell & Norvig, 2009). The present study focuses on intelligent DSS which are agent-assisted (for an extensive overview of agent types see, for example, Nwana, 1996).

The degree to which a system is enabled to process a certain task on behalf of a human has been defined as LOA (e.g. Endsley, 2017). Sheridan and Verplank (1978) initially proposed ten levels, ranging from level 1: the human completing the task and then turning it over to the computer, to level 10: the computer completing the task, deciding how it should be done, and subsequently informing the human if the computer perceives it as important for the human to be informed. Kaber and Endsley (1997, 2004) extended this taxonomy by including four task stages of information processing: information monitoring, option generation, action selection, and implementation. Building on models of human information processing, Parasuraman et al. (2000) proposed a similar model, differentiating: Information acquisition, information analysis, decision selection, and action implementation. Based on the taxonomies proposed by Kaber and Endsley (1997, 2004) and Parasuraman et al. (2000), we will differentiate four levels of task processing: (1) Monitoring and information presentation, (2) generation of options, (3) decision making and selection of course of action, and (4) implementation of action. Each task stage can either be shared between the human user and the system or be performed by either one of them. Onnasch et al. (2014) further argue that high automation can be represented by both a higher level of automation and automation of later task stages, which are typically preceded by automation of earlier stages. This implies that a combination of higher levels and a greater number of stages will also result in high automation.

As automation is given more leeway to perform tasks and make decisions without requiring human involvement, it becomes increasingly autonomous (Endsley, 2017; O'Neill et al., 2020; Parasuraman et al., 2020). Endsley (2017) defines *high autonomy* as users having no control over task processing. This corresponds with Parasuraman and Riley's (1997) level 7 and above, where "the automation carries out a function and informs the operator to this effect, but the operator cannot control the output" (p. 232; see also O'Neill et al., 2020). *Partial autonomy* has been described as high automation which requires approval by a human (see levels 5 and 6 in Parasuraman & Riley, 1997) while *low autonomy* describes automation which is focused on providing information to the user (levels 2–4; "technology as a tool"). Endsley (2017) further proposes a taxonomy of three stages of task performance (situation awareness, decision, action) that will impact users differently, depending on the level of autonomy.

In line with previous authors (Endsley, 2017; Parasuraman & Riley, 1997), we suggest that the level of autonomy is impacted by both the number of and the type of task stages that are automated. Hence, systems with a high LOA will, in many cases, also have a higher level of autonomy. This is particularly the case for automation of later task stages, such as selecting decisions or implementing actions. With increasing capabilities, today's DSS tend to be developed with a high LOA for a specific type of task (e.g. filtering information). This can be interpreted as a high LOA of a task stage. Using DSS at work which are enabled to process multiple task types or stages can lead to a shift in agency between the system and the employee. For example, a DSS with high autonomy may take over complete information processing tasks (e.g., processing new incoming customer information and sending a response), leaving little to no control to the employee.

In the work context, the use of highly competent technical systems (often having high autonomy) has been associated with negative outcomes such as users perceiving a lack of control, increases in perceived workload, negative perceptions of the technology, as well as technology-related stress (Day et al., 2012; Parker & Grote, 2020). To gain a better understanding of how employees interact with autonomous systems, it is crucial to understand how autonomy impacts user reactions. Even though DSS are highly beneficial for aiding employees in information or task processing, it is not clear under which conditions autonomy can lead to negative cognitive, affective, and behavioral reactions towards the system (Eymann, 2013; Flemisch et al., 2012).

1.2. Effects of autonomy on users

Despite the increased use of agent technologies (e.g. as part of email programs), many organizations still report problems regarding employee interaction (Parker & Grote, 2020). A central motivation for implementing DSS is to increase employee performance and decrease workload by delegating information processing tasks. Yet, employees' subjective perceptions of these systems may differ from their objective benefits. Therefore, it will be essential to understand how DSS with differing autonomy are initially perceived by employees and how these perceptions relate to how DSS are used.

1.2.1. Information overload

Employees' high information processing requirements are a central challenge for today's highly digitalized organizations and are associated with stressors such as high workload and stress (Day et al., 2012). When employees experience an imbalance between their information processing requirements and their capacities, this can lead to information overload (Eppler & Mengis, 2004). Research suggests that this imbalance can either be addressed by improving an individual's information processing competencies (e.g. time management training) or by employing methods to decrease information processing requirements (i.e. amount of information). Delegating information processing tasks to DSS has been shown to be one of the most successful methods to counteract information overload (Eppler & Mengis, 2004). Although using DSS offer clear benefits for employees' information and workload (Onnasch et al., 2014), the delegation of information processing tasks has also been associated with both mental underload, when many task stages are delegated (Wang et al., 2020), or increased mental workload, in systems with high LOA (Balfe et al., 2012, 2015). Whether an employee perceives the DSS as beneficial may depend on numerous factors, but will be strongly impacted by the employee's evaluation of the system's capabilities (Glikson & Woolley, 2020). When a system is newly introduced, users will base this initial evaluation on prior experiences with similar technologies (Ulfert & Georganta, 2020). Thus far it is unclear though how employees perceive DSS with different autonomy regarding their potential for reducing information load. Particularly DSS which independently take over many task stages (high autonomy), should be perceived as decreasing information load, as objective information processing requirements are decreased (see also Endsley, 2017). It is therefore assumed that the level of autonomy is related to the level of experienced information load.

Hypothesis 1. proposes a negative relationship between autonomy and experienced information load reduction, specifically, we assume that an increasing degree of autonomy is associated with decreasing information load.

1.2.2. Technostress

Although DSS use is positively associated with reducing information processing requirements, users can experience technology-related stress (technostress; Ayyagari et al., 2011; Brod, 1984; Riedl et al., 2012). Technostress results from a user's evaluation of a system's characteristics (Ayyagari et al., 2011). Day et al. (2010, 2012) describe technology-related stress to be a consequence of increased demands, such as a lack of control, resulting from the technology's characteristics. Referring to theories of occupational stress and job control (e.g. Bakker & Demerouti, 2007; Dwyer & Ganster, 1991; Hair et al., 2007), they argue that employees that lack control over their work environment, such as task characteristics, will experience higher levels of anxiety, frustration, and stress. For instance, in the context of email use, a lack of control was associated with stress (Hair et al., 2007). Findings from HCI research further underline the importance of control. Particularly a high dependency on the system, a high gap between the user's required and actual technological skills, and high complexity of the system contribute to technostress (Ragu-Nathan et al., 2008). All three aspects have been described to increase with high system autonomy and LOA (Lyons & Havig, 2014). Based on these findings, we argue that employees will perceive high autonomy DSS as having high control over how a task is processed. This experience of shifting control from oneself to the DSS may be perceived as stressful, as employees may not always be able to manually change how a task is processed. Consequently, we argue, that a higher DSS autonomy is associated with higher levels of experienced technostress:

Hypothesis 2. There is a positive relationship between autonomy and users' experienced technostress when using DSS. We assume that increasing autonomy is associated with increasing levels of technostress.

1.2.3. User intention

Users'willingness to interact with and use a technology is based on perceptions of the technology's usefulness and its ease of use (see also Technology Acceptance Model, TAM, UTAUT; Beaudry & Pinsonneault, 2005; Venkatesh, 2000; Venkatesh & Bala, 2008). These attitudes are critical, especially when DSS are newly introduced, as they impact effective system use. Venkatesh and colleagues (2008; 2016) further suggest including central influencing factors on user intentions, such as perceived control. Their argument is in line with prior assumptions on the relationship between perceived control over behavioral outcomes and behavioral intentions (see e.g. theory of planned behavior; Ajzen, 1985, 2002). Some authors have suggested that particularly autonomy has an impact on users' positive or negative perceptions of a technology which can consequently impact user intentions (Norman, 1994). This is further supported by research on user interaction with autonomous cars where low autonomy has been associated with positive perceptions of the technology and higher user intentions (Beier et al., 2006; Kruijff, 2012). Similarly, it has been suggested that systems with intermediate rather than high levels of autonomy are most beneficial for users (Endsley, 2016). We thus argue that the described findings can be transferred to using DSS at work.

Hypothesis 3. There is a negative relationship between autonomy and the intention to use a DSS. We assume that increasing levels of autonomy are associated with a decreasing intention to use the DSS.

1.2.4. The role of experience

Individuals differ in how they process large loads of information (Eppler & Mengis, 2004) as well as in their reactions towards DSS characteristics, such as autonomy (Endsley, 2016). Cognitive, affective, and behavioral user reactions have particularly been linked to individual differences that relate to technology use in general (e.g. computer anxiety) or to the situation or task (e.g. relevance of the technology for processing a task; Venkatesh & Bala, 2008). These differences particularly impact individuals' initial evaluation of a technology, significantly impacting their user reactions (Ayyagari et al., 2011; Endsley, 2017; Yu et al., 2017). The technology acceptance model (TAM; UTAUT; Venkatesh et al., 2003, 2016; Venkatesh & Bala, 2008) specifically highlights the moderating role of experience (esp. experience with a system) on the relationship between users' perceptions of a system and users' behavioral intentions. Especially in users with high levels of experience, behavioral intentions will be less affected by their initial perceptions of the system (e.g. ease of use). Similarly, a high quantity of incoming digital information (e.g. emails) does not in all cases lead to individuals experiencing information overload. Individuals with more experience in using a system, often show a lower risk of information overload and are more likely to perceive a system as useful (Ayyagari et al., 2011; Venkatesh & Bala, 2008). Although the role of experience has been addressed in central models of HCI (e.g. TAM), there is still a lack of differentiation of the construct in the literature. While some authors have addressed experience as referring to prior technology use (e.g. frequently using technologies at work; Shu et al., 2011; Venkatesh & Bala, 2008), other authors have addressed job experience (e.g. years of working as a medical specialist) as a central influencing factor when using DSS (Lee & See, 2004; Madhavan et al., 2006; Manzey et al., 2009). With increasing autonomy, agency over tasks and roles shift from the employee to the DSS (Larson & DeChurch, 2020). This impacts both the collaboration with the DSS as a technology as well as the DSS as a replacement for the employee. We thus propose that both technology (i.e. experience in technology use) and job experience (i.e. duration of being employed in a job or position) impact initial user reactions towards a system.

The *person-technology fit framework* (Ayyagari et al., 2011) proposes that individual differences, such as prior technology use (i.e. technology experience), impact how an individual perceives a system's characteristics. A gap between the system and the person (e.g. due to high complexity of the system) leads to a misfit, which is reflected as stressors, such as the experience of overload or technostress (Ayyagari et al., 2011; Tarafdar et al., 2011). Similarly, the TAM suggests that technology experience impacts perceptions of the system and consequently, user intentions (Venkatesh & Bala, 2008). In line with previous research (Ayyagari et al., 2011; Venkatesh & Bala, 2008), we argue that individuals' experience with technology impacts this initial perception of and consequently reactions to DSS characteristics, and especially its autonomy and propose that:

Hypothesis 4. Technology experience buffers the relationship between autonomy and experienced information load reduction, expected technostress, and intention to use the DSS. Interacting with high autonomy DSS, individuals with high technology experience expect more information load reduction, expect less technostress, and have a higher intention to use the DSS.

In contrast, research findings on the relationship between job experience on user reactions are mixed (Ulfert & Scherer, 2020). On the one hand, studies have reported that individuals with lower job experience react more positively towards highly autonomous systems (e.g. Reinders et al., 2015). On the other hand, it has been shown that experts are quicker to rely on DSS recommendations (Chavaillaz et al., 2019), while novices may be less likely to detect false recommendations (Arnold et al., 2004). In general, low job experience has been related to feelings of insecurity (Chase & Ericsson, 1981; Gruber, 2007; Lindquist & Whitehead, 1986; Morgan & Pearson, 2002; Shamir & Drory, 1982). Individuals with high job experience are less affected by uncertain situations, such as the introduction of a new technology (Chi, 2006). Based on the person-technology fit framework we argue that when DSS are used in the work context, an individuals' job experience should also impact how a systems' characteristics are perceived. This is because individuals with high job experience will feel less insecure and are less affected by uncertain situations, such as delegating tasks to a DSS. Hence, we argue that when working with DSS in work contexts, individuals' expected reduction of information load, technostress, and intention of using the DSS may vary depending on their level of job experience. Job experience should thus be explored as a moderating variable. We propose that:

Hypothesis 5. Job experience buffers the relationship between autonomy and experienced information load reduction, expected technostress, and intention to use the DSS. Interacting with high LOA DSS, individuals with high job experience expect more information load reduction, expect less technostress, and have a higher intention to use the DSS.

As previously noted, DSS strongly vary in how they are used in the work context. While some DSS are enabled to take over complete tasks with varying demands (e.g. analyzing medical images and making suggestions about potential treatments), some only offer a limited scope (e.g. making suggestions about the importance of an email). It is likely that when DSS are enabled to complete a diverse range of task types, users will require higher levels of technology or job experience to understand the system's functioning and to intervene when system failures occur (e.g., when having to switch to manual control due to a technical error; see e.g., Ironies of Automation; Bainbridge, 1983). However, while HCI research highlights the impact of contextual factors on user reactions (Endsley, 2017; Sheridan, 2019), it is unclear how systems that differ in their capabilities for task processing impact user reactions. To gain initial insights and to explore how these different capabilities could impact user reactions, the present study will investigate the proposed relationships in two different DSS: (1) using a system that is able to process multiple task types (i.e. taking phone calls and selecting actions) and (2) using a system that is able to process a single task type (e.g. only processing email by relevance).

1.3. *The present studies*

In this paper, two experimental vignette studies (see Fig. 1) were conducted to systematically investigate the effects of autonomy on user reaction.[1] Additionally, we considered experience as a moderating factor on this relationship. In study 1, we investigated the effects of technology experience on the relationship between autonomy and user reactions. In study 2, we experimentally varied the level of job experience. Following the taxonomies suggested by Parasuraman and Riley (1997) and Endsley (2017), in study 1, vignettes were used to manipulate agent autonomy by varying the number of task stages with high LOA. In study 2, agent autonomy was manipulated with regard to the operator control (full autonomy, partial autonomy, no autonomy). Due to the large differences in DSS that are used in organizations today, in study 1, the vignette describes a system that is able to process different types of tasks (e.g. answering calls, selecting actions), whereas, in study 2, the vignette describes a system which can only process one specific type of task (i.e. processing content of emails).

2. Study 1 – effect of technology experience in a multiple task DSS

2.1. *Method*

2.1.1. *Sample*

A total of $N = 244$ people participated in the online experimental vignette study. Access to the online study was distributed through different online channels such as professional networking platforms and mailing lists. The sample consisted of $N = 162$ student and $N = 82$ non-student participants (62.7% female; $M_{age} = 28.79$, $SD = 11.34$). The student sample consisted of participants from a German university, from varied fields of studies (40% of student participants indicated the field of social sciences), and different semesters (ranging from semester 1 to 12). The non-student sample consisted of participants from diverse occupational fields (14% indicated being from the field of academia, another 14% were from the field of health or social work) and differing levels of work experience (ranging from less than two years work experience to over 30 years). A total of 26.2% of the sample indicated prior knowledge of agent-assisted DSS, 4.1% indicated to have previously worked with an agent-assisted DSS.

2.1.1.1. Control variables. To control for interindividual differences in the sample due to prior experiences with DSS, we included the following two questions as control variables: "*Have you previously heard about autonomous decision* support *systems which utilize artificial intelligence (AI) as the one described?*" (1 = *yes*, 2 = *no*) and "*Have you previously used an autonomous decision* support *system that uses AI?*" (5-point Likert scale from 1 = *never* to 5 = *always*). Prior experience was measured at the end of the questionnaire.

2.1.2. *Procedure*

The present study used an experimental vignette scenario (Aguinis & Bradley, 2014; Karren & Barringer, 2002; Rossi & Nock, 1982; Wallander, 2009) to systematically investigate the effects of LOA on information load reduction, technostress, and intention of using the DSS. In the following, we first describe the vignette method, followed by the development of the vignette scenarios of this study.

2.1.2.1. Vignette method. Experimental vignette studies have been shown to be an effective and economical method in organizational research for assessing behaviors, attitudes, and intentions (Aguinis &

[1] Both studies were conducted as part of a larger (unpublished) research project. Power analyses were performed for the overall project and thus exceed the sample sizes required for testing the proposed relationships.

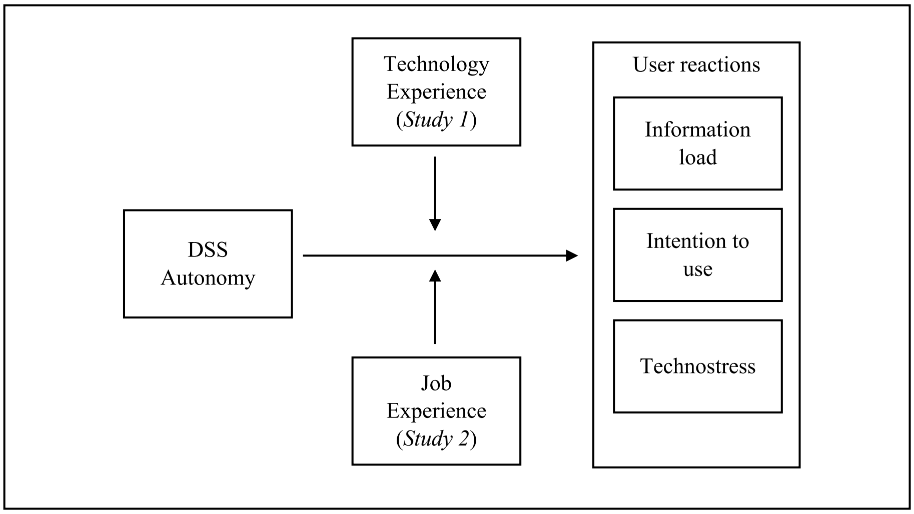

Fig. 1. Moderating effect of technology and job experience on the relationship between autonomy and user reactions.

Bradley, 2014; Karren & Barringer, 2002; Kristof-Brown et al., 2002). Participants are asked to respond to a series of hypothetical scenarios in which the independent variables are manipulated (Aiman-Smith et al., 2002; Karren & Barringer, 2002). This is particularly useful when studying phenomena that cannot easily be studied in field settings as for instance the use of highly autonomous DSS at work. Additionally, using vignette scenarios overcomes some limitations of other research designs (Wang et al., 2015).

Firstly, studying work-related behaviors and perceptions in field studies comes with a multitude of confounding variables, such as work environment or task characteristics, which potentially poses problems of (multi-)collinearity (Rotundo & Sackett, 2002; Wang et al., 2015). The vignette technique thus offers the benefit of studying reactions towards DSS in a controlled environment. Secondly, it has been argued that when rating vignette scenarios, individuals base their ratings (e.g., "I am willing to use this DSS") on cognitive processes not explicitly aware to the individual. In contrast, directly asking individuals (e.g., "Would you be willing to use an intelligent DSS") has been argued to lead to less accurate results (Wang et al., 2015). Specifically, for the present study, this is a benefit of the vignette technique. As most individuals are still unfamiliar with using intelligent DSS at work, asking for a direct opinion on the matter might increase the likelihood of inaccurate responses. The vignette technique thus serves as an appropriate method for this study.

To design the scenarios, we followed common procedures recommended in vignette literature (Aiman-Smith et al., 2002; Karren & Barringer, 2002) and used expert interviews to gain detailed descriptions of DSS properties. Furthermore, as recommended by Karren and Barringer (2002), we provided participants with a general description of the work place as the first part of the scenario in which the majority of information was held constant across the scenarios.

2.1.2.2. Development of the vignette and pilot study. The setting of the vignette scenario[2] was at the individual's fictive work place. Following recommendations by Aguinis and Bradley (2014) for vignette design, a broad work scenario was chosen, which does not require any specific skills or knowledge, in this case, being employed to answer and process customer requests via phone and email. The scenario contained information about: (1) the setting of the work station in an open space office, (2) the content of the work, as well as (3) examples of daily tasks such as taking customer calls, answering emails, and taking part in meetings.

After the description of the work setting and job description, a new telephone assistant tool was described. The described tool automatically takes customer calls and sorts incoming information. Depending on the settings of the system, it can further process the incoming information, suggest next possible steps, and even return calls. By observing the user's behavior, it improves its decision making over time.

2.1.2.3. Manipulation. Agent Autonomy. Based on prior research on LOA and agent autonomy (Kaber & Endsley, 1997, 2004; Parasuraman et al., 2000), the vignettes contained four different task stages that could be taken over by the DSS: (1) Monitoring and information presentation, (2) generation of options, (3) decision making and selection of course of action, and (4) implementation of action (see Fig. 2). LOA 1 represented only the first task stage being processed by the DSS while LOA 4 represented all task stages being processed by the DSS. Later task stages were associated with higher autonomy, as less or no decisions by the user were allowed in task processing (e.g. selecting the course of action). In this study, high LOA was thus associated with high agent autonomy.

2.1.2.4. Pretest and online implementation of the vignette study. In a cognitive pretest $N = 5$ participants were asked to read the vignette scenarios while thinking aloud (think aloud method). Afterwards, they were asked to rate the level of automation of the different scenarios from lowest to highest. Additionally, participants rated the degree to which the scenario was realistic and imaginable. Results indicated that participants were able to differentiate between different levels of control as intended, ranking LOA 4 as having the highest level of agent autonomy and LOA 1 as having the lowest level of autonomy. Furthermore, scenarios were rated and described to be comprehensive, realistic, and imaginable.

The online study compared four levels of LOA, as represented in Fig. 2. This results in a total of four vignettes that participants were asked to rate concerning their expected reduction of information load, technostress, and intention of using the DSS. In order to avoid sequence effects, the order of the vignettes was randomly varied between participants. This repeated measure design offers the benefit of controlling for inter-individual variance thus decreasing error variance and increasing statistical power (Rasch et al., 2006).

2.1.3. Measures

All dependent variable measures were administered after each of the four vignettes.

Reduced information load. The subjective expectation of information load reduction due to using the DSS was based on the *Overload Scale* by Schultz and Vandenbosch (1998). The original scale asks for increases in

[2] A sample vignette can be found in the electronic supplement 1.

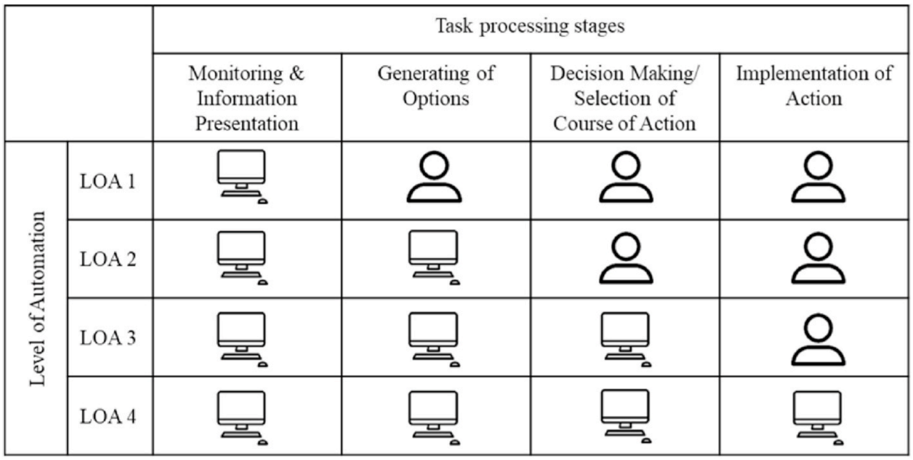

Fig. 2. Experimental design describing levels of automation (LOA) and corresponding task processing stages delegated to the system. Automation of all task stages was associated with high autonomy, automation of early task stages was associated with lower autonomy.

information load due to technology use. In the present study, these seven items were reversed, now asking for the reduction of information load (Sample item "*I receive less information that distracts me from my work*"). The measure uses a 5-point Likert-scale from 1 (*strongly disagree*) to 5 (*strongly agree*).

Technostress. The extent to which participants expected to experience technostress based on LOA settings was measured using three items from the strain subscale (Moore, 2000) adapted by Ayyagari et al. (2011; e.g., "*I perceive working with the tool as a strain*"). Scale scores could range from 1 ("*strongly disagree*") to 5 ("*strongly agree*"). One item was excluded as it did not fit the context of the vignette (strain based on working with the technology for a whole day).

Intention of using the DSS. The decision of using the assistance system based on its settings was measured with a single item scale ("*Assuming I have access to the system, I intend to use it*") by Venkatesh and Davis (2000; 5-point Likert scale 1 = *strongly disagree* to 5 = *strongly agree*).

Technology experience. Additionally, in the beginning of the questionnaire, participants were asked to rate their general experience in using technology (5-point Likert scale from 1 = *low* to 5 = *high;* Ulfert et al., 2020).

2.2. Results

2.2.1. Descriptive statistics and preliminary analysis

Means, SDs, Cronbach's alpha, and bivariate correlations are reported in Table 1. Cronbach's alpha for reduced information load and technostress were acceptable ranging between $\alpha = 0.73$ and $\alpha = 0.87$. No significant differences were found between the student and the non-student sample. As no significant differences were found between participants with or without prior experience with autonomous support systems, prior experience with DSS was not included as a control variable for hypotheses testing.

2.2.2. Hypotheses testing

We analyzed the data using R (R Core Team, 2013; version 3.6.0) and *lme4* (Bates et al., 2012) to perform three mixed repeated measure ANOVAs. As fixed effects we entered LOA and technology experience into the model. As random effects, we added intercepts for subjects (see Table 2).

Hypothesis 1 assumed that with increasing levels of autonomy, levels of information load would decrease and thus ratings of expected information load reduction would increase. When comparing the four levels of LOA, mean information load reduction (see Table 1) differed in the expected direction. Consistent with Hypothesis 1, LOA 1, 2 and 4 were associated with mean ratings of information load reduction in the expected direction (from low to high). However, differences in mean scores were only small. Additionally, at LOA level 3, mean ratings of information load reduction were the lowest, indicating that participants perceived LOA 3 as less beneficial for information processing. The main effect of autonomy on information load reduction was not significant; $F(3, 726) = 2.22$, $p = .09$, $\eta_p^2 = 0.01$. Post hoc comparison of means (*Bonferroni* corrected) revealed that although most autonomy conditions significantly differed (all *ps* = .001-.02), no significant difference was found at LOA 1 and LOA 2 as well as between LOA 2 and LOA 4. Hypothesis 1 was thus not supported.

Hypothesis 2 proposed that autonomy is positively related to expected technostress, with high autonomy being associated with high technostress. Results showed highest mean ratings of expected technostress at LOA 3 and 4 and lowest ratings of technostress at LOA 1. However, no significant main effect was found for the effect of autonomy on technostress; $F(3, 726) = 1.75$, $p = .16$, $\eta_p^2 = 0.01$. Post hoc comparison of means (*Bonferroni* corrected) revealed that although most autonomy conditions significantly differed (all $ps < .001$), no significant difference was found between LOA 1 and LOA 2 as well as between LOA 3 and LOA 4. Hypothesis 2 was rejected.

In Hypothesis 3, we assumed a negative relationship between autonomy and the intention of using the DSS, with high autonomy being associated with a low intention of using the DSS. Table 1 shows that the intention of using the DSS was indeed highest in the level 1 LOA scenario compared to level 3 and 4 LOA vignette scenarios. Again, LOA 3 was rated the least positive, having the lowest mean score for user intention. There was a significant main effect for autonomy, however the effect size was small; $F(3, 726) = 3.24$, $p = .02$, $\eta_p^2 = 0.01$. Post hoc analysis (*Bonferroni* corrected) revealed that most LOA conditions significantly differed (all $ps < .001$; LOA 3 – LOA 4, $p = .02$), with no significant difference between LOA 1 and LOA 2. Hypothesis 3 was confirmed, showing a negative relationship between autonomy and user intention.

It was further assumed (Hypothesis 4) that technology experience moderates the relationship between autonomy and user reactions. In contrast to this assumption, no significant moderating effects were found. Nevertheless, analysis revealed a significant main effect of technology experience on technostress $F(1, 242) = 16.36$, $p < .001$, $\eta_p^2 = 0.02$ as well as user intention $F(1, 242) = 10.67$, $p < .001$, $\eta_p^2 = 0.01$. Hypothesis 4 was rejected.

With the exception of Hypothesis 3, all Hypotheses were rejected. Furthermore, all of the reported analyses had only small effect sizes.

Table 1
Study 1. Cronbach's alpha, means, standard deviations, and inter-correlations of the dependents variables.

Measures	A	*M*	*SD*	Level of Automation										
				1		2		3		4				
				M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	1	2	3
1 Technology experience		3.46	0.82											
2 Information load reduction	.85–.87			3.81	0.82	3.83	0.84	3.65	0.86	3.96	0.83	.048 [-.08, .17]		
3 Technostress	.73–.83			2.24	0.80	2.30	0.80	2.76	0.87	2.71	0.90	-.252** [-.37, −.13]	-.360** [-.46, −.25]	
4 Intention of using DSS				3.77	1.06	3.66	1.09	2.66	1.27	2.90	1.32	-.205** [.08, .32]	.467** [.36, .56]	-.542** [-.63,-45]

Notes. $N = 244$. $^{**}p < .01$ (two-sided).

Table 2
Mixed repeated measures ANOVAs study 1.

	SS	df	MS	F	p	*Partial* η^2	*Partial* η^2 90% CI [LL, UL]
Information load reduction							
Autonomy	2.14	3	0.71	2.21	.085	.009	[.00, .02]
Technology Experience	0.18	1	0.18	0.56	.454	.001	[.00, .02]
Technology Experience x Autonomy	0.52	3	0.17	0.53	.658	.002	[.00, .01]
Technostress							
Autonomy	1.89	3	0.63	1.75	.156	.007	[.00, .02]
Technology Experience	5.89	1	5.89	16.36	.001***	.021	[.02, .12]
Technology Experience x Autonomy	0.82	3	0.27	0.76	.518	.003	[.00, .01]
Intention of using DSS							
Autonomy	8.14	3	2.71	3.24	.022*	.012	[.00, .03]
Technology Experience	8.93	1	8.93	10.67	.001**	.013	[.01, .09]
Technology Experience x Autonomy	0.80	3	0.80	0.32	.812	.001	[.00, .00]

Notes. $N = 244$. LL and UL represent the lower-limit and upper-limit of the partial η^2 confidence interval.

3. Study 2 – effects of job experience in a single task DSS

3.1. Method

3.1.1. Sample

In total $N = 500$ people participated in the online experimental vignette study. Access to the online study was distributed through different online channels such as professional networking platforms and mailing lists. The sample consisted of $N = 362$ student and $N = 138$ non-student participants (63% female; $M_{age} = 26.57$, $SD = 8.03$). The student sample consisted of participants from different German universities, varied fields of studies (45% of student participants indicated the field of social sciences), and different semesters (ranging from semester 1 to 9). The non-student sample consisted of participants from diverse occupational fields. A total of 30.04% of the sample indicated prior knowledge of intelligent DSS. Participants were distributed to the vignette scenario depending on their current position (student or non-student) by filtering questions.

3.1.1.1. Control variables. Again, prior experience with DSS was assessed as a control variable. The same measure as in study 1 was implemented.

3.1.2. Procedure

3.1.2.1. Development of the vignette and pilot study. As in study 1, the setting of the vignette scenario[3] was at the individual's fictive work place. Two different work scenarios were developed based on the specifics of the sample (scenario 1, student sample: working as a student tutor; scenario 2, non-student sample: working as a project manager). The contexts of the scenarios were described according to these two jobs (student tutor and project manager) and contained information about: (1) the quantity of parallel projects and activities the role includes, (2) the daily minimum quantity of emails (50 emails), as well as (3) examples of email content (e.g., newsletter, questions, or customer requests).

After the description of the work setting and job description, a new email tool, offered by the employer, was described. The described tool automatically sorts low quality and low priority emails, based on the user's previously set preferences, such as certain key words as well as learning mechanisms based on the DSS observations of the user's behavior over time. To manipulate autonomy, the DSS was described with different settings of operator control that can be chosen by the user. Additionally, the level of job experience was varied between vignettes.

3.1.2.2. Manipulations. Agent Autonomy. The described DSS differed from study 1 with regards to the type of task to be processed (focused on processing email relevance only) as well as regarding the operationalization of agent autonomy. In study 2, the vignettes contained three different levels of DSS actions which varied in operator control and thus agent autonomy: (1) *No autonomy*: the DSS highlights emails for suggesting content of low importance, (2) *Partial autonomy*: DSS automatically moves emails to the trash folder which can be further processed by the user (3) *full autonomy*: DSS processes emails based on relevancy and deletes emails permanently without the user being able to override the decision. In the taxonomy of Parasuraman and Riley (1997), these actions would represent automation level 2–4, level 5–6, and level 7 and above respectively.

Job experience. Two different levels of job experience were systematically varied between the vignettes. (1) Low level job experience was described as being in the specified role for just a few days. (2) High level job experience was described as being in the specified role for multiple months. The level of job experience was presented as part of the scenario's cover story.

3.1.2.3. Pretest and online implementation of the vignette study. In a cognitive pretest $N = 11$ participants were asked to rate agent autonomy

[3] Samples of the different vignettes can be found in the electronic supplement 1.

in each scenario, the degree to which the scenario seemed realistic and imaginable, as well as the level of job experience of the described scenario. Participants were able to differentiate the degree of autonomy and job experience as intended. Furthermore, scenarios were rated to be comprehensive, realistic, and imaginable.

The online study was set up according to a 2 × 3 factorial design (high job experience vs. low job experience x low (highlight emails) vs. partial (move emails) vs. full (delete emails) autonomy. This results in a total of 6 vignettes that participants were asked to rate concerning their expected reduction of information load, expected technostress, and intention of using the DSS. In order to avoid sequence effects, the order of the manipulations (autonomy and job experience) were randomly varied between participants.

3.1.3. Measures

All dependent variable measures were administered after each of the six vignettes. To assess reduced information load, technostress, and intention to use, the same measures were used as in study 1.

3.2. Results

3.2.1. Descriptive statistics and preliminary analysis

Scale means, standard deviations, and inter-correlations of all dependent variables are presented in Table 3. Cronbach's alpha for reduced information load and technostress were both acceptable with α = 0.79. No significant differences were found concerning the student and the non-student sample or prior experience with DSS. Prior DSS use was therefore not included in the analysis. Additionally, there was no significant difference in the outcome variables between the student and non-student sample.

3.2.2. Hypotheses testing

As in study 1 we used R (R Core Team, 2013) and *lme4* (Bates et al., 2012) to perform mixed two-way repeated measure ANOVAs. As fixed effects we entered autonomy and job experience into the model. As random effects, we added intercepts for subjects.

Hypothesis 1 assumed that with increasing autonomy, levels of information load would decrease and thus ratings of expected information load reduction would increase. When comparing autonomy levels (low, partial, full), the means of information load reduction (see Table 3) differed in the expected direction with a significant main effect, F (2, 2495) = 504.02, $p < .001$, $\eta_p^2 = 0.27$. Post hoc comparison of means (*Bonferroni* corrected) showed significant differences in expected information load ratings between all three levels of autonomy (all ps = .001-.002). Thus, results showed a negative relationship between autonomy and expected information load reduction, supporting Hypothesis 1.

Hypothesis 2 proposed that autonomy is positively related to expected technostress, with high autonomy being associated with high technostress. Analysis showed highest ratings of expected technostress with high autonomy and lowest ratings of technostress with low autonomy (see Table 3). There was a significant main effect of autonomy on expected technostress $F\,(2, 2495) = 518.91, p < .001; \eta_p^2 = 0.37$. Post hoc comparison of means (*Bonferroni* corrected) indicate significant differences of expected technostress between autonomy scenarios (all ps < .001). As results indicate a positive relationship between autonomy and technostress, Hypothesis 2 was also supported.

In Hypothesis 3, we assumed a negative relationship between autonomy and the intention of using the DSS with low levels of autonomy being associated with high intention of using the DSS. Table 3 shows that the intention of using the DSS was indeed highest in the low autonomy scenario compared to the full autonomy scenario and medium ratings in the partial autonomy scenario (significant main effect, F [2, 2495] = 1071.07, $p < .001$, $\eta_p^2 = 0.44$). Ratings of user intention (post hoc comparison of means, *Bonferroni* corrected) differed significantly between the three autonomy scenarios (all $ps < .001$). As findings show a negative relationship between autonomy and intention of using the DSS, Hypothesis 3 was also supported.

Further, we analyzed the moderating role of job experience on expected information load, expected technostress, and intention of using the DSS (Hypothesis 5). Concerning job experience, interaction effects were confirmed (Information load reduction: F [2, 2495] = 6.85, $p < .001$; $\eta_p^2 = 0.01$; Technostress: F [2, 2495] = 18.45, $p < .001$; $\eta_p^2 = 0.01$; User intention: F [2, 2495] = 27.58, $p < .001$; $\eta_p^2 = 0.02$). Post hoc analysis (*Bonferroni* corrected) confirmed significant differences between the high and the low tenure condition (all $ps < .001$), revealing a significantly greater information load reduction, lower technostress, and higher user intentions in individuals in the high job experience condition. Therefore, Hypothesis 5 was confirmed.

Analyses confirmed all of the proposed relationships. At the same time, effect sizes (see Table 4) indicate that particularly autonomy is a predictor of user reactions, compared to the interaction between autonomy and job experience.

4. Discussion

The aim of the present study was to extend current research on the use of DSS at work by highlighting the effect of DSS autonomy. Specifically, the present study aimed to differentiate the effects of autonomy on cognitive, affective, and behavioral user reactions. Based on HCI and psychological stress research, in two vignette studies, we tested the effects of autonomy, represented by different task stages (study 1) and different levels of user control (study 2), on users' information load, technostress, and user intention. Furthermore, we studied the moderating effect of technology and job experience in two different types of DSS. In line with our hypotheses, we found high autonomy to be associated with high information load reduction. However, with increasing

Table 3
Study 2. Cronbach's alpha, means, standard deviations, and inter-correlations of the dependents variables.

Measures	Job experience	*α*	Autonomy							
			low		partial		full			
			M	*SD*	*M*	*SD*	*M*	*SD*	1	2
1 Information load reduction	Low		2.84	1.01	3.64	0.87	3.77	0.89		
	High		2.92	1.07	3.95	0.78	4.08	0.78		
	total	.79	2.88	1.04	3.80	0.70	3.92	0.71		
2 Technostress	Low		2.19	1.01	2.92	1.06	3.66	1.03		
	High		1.76	0.79	2.15	0.95	3.14	1.01		
	total	.79	1.98	0.75	2.54	0.85	3.40	0.09	-.114* [-.21, −.02]	
3 Intention of using DSS	Low		3.98	1.12	2.79	1.24	1.42	0.88		
	High		3.82	1.19	3.28	1.34	1.87	1.20		
	total		3.90	0.95	3.04	1.10	1.64	0.82	.375** [.29, .45]	-.353** [-.45,-25]

Notes. $N = 500$. *$p < .05$ (two-sided). **p < .01. ***$p < .001$ (two-sided).

Table 4
Mixed repeated measures ANOVAs Study 2.

	SS	df	MS	F	p	*Partial η^2*	*Partial η^2* 90% CI [LL,UL]
Information load reduction							
Autonomy	646.58	2	323.29	504.02	.001***	.273	[.26, .31]
Job experience	41.22	1	41.22	64.27	.001***	.023	[.02, .04]
Job experience x Autonomy	8.79	2	4.40	6.85	.001***	.005	[.00, .01]
Technostress							
Autonomy	1037.82	2	518.91	781.57	.001***	.373	[.36, .41]
Job experience	249.41	1	249.41	348.85	.001***	.125	[.11, .15]
Job experience x Autonomy	15.40	2	7.70	18.45	.001***	.009	[.00, .02]
Intention of using DSS							
Autonomy	2585.35	2	1292.68	1071.07	.001***	.436	[.44, .48]
Job experience	50.18	1	50.18	41.58	.001***	.015	[.01, .03]
Job experience x Autonomy	66.58	2	33.29	27.58	.001***	.019	[.01, .03]

Notes. $N = 500$. LL and UL represent the lower-limit and upper-limit of the partial η^2 confidence interval.

autonomy, participants reported higher levels of technostress and lower intentions of using the DSS. Only in study 2, the proposed effect of autonomy on user reactions was confirmed.

Information load reduction was assumed to be highest when more task stages were automated by the DSS and the system had full autonomy (Hypothesis 1). Indeed, expected reduction of information load was highest when DSS were described with high autonomy. Increasing levels of DSS autonomy allow users to delegate tasks without being required to take further user action, thus decreasing information processing requirements. Results also indicate that the type of task stage that is delegated to the system may impact user reactions. In study 1, LOA 3 (i. e. the system takes over the first three task stages, the user performs the last ask stage) resulted in the lowest mean ratings of information load reduction across all autonomy conditions. Although the effect of autonomy on information load reduction was confirmed in study 2, no significant effect was found in study 1. This may have particularly resulted from the DSS in study 1 generally being described as decreasing information load more than the DSS described in study 2. In general, DSS with increasing autonomy can be considered beneficial to users by decreasing risks of information overload. However, when receiving preset action plans by the systems, this can potentially increase perceived information load. This is in line with prior studies, which have associated high LOA with high levels of mental workload (Balfe et al., 2015). One potential reason for this could be that employees still feel required to check and compare the action plans suggested by the system. Since the employee is still responsible for executing the action (e.g. calling back a customer and suggesting a product), they might still face potential consequences from the action. The question of who is responsible for a system's actions is highly relevant, especially as more autonomous systems are used in many areas of life (e.g. autonomous cars). Further research is needed to explain this mechanism.

Furthermore, we argued that while a reduction of information load is beneficial to users, delegating tasks to autonomous systems also comes with drawbacks. In both studies participants were expecting to experience higher levels of ***technostress*** when autonomy was high. However, Hypothesis 2 was only supported in study 2. In study 1, mean expected technostress was highest at LOA 3 compared to all other levels. As stated in previous studies (e.g. Flemisch et al., 2012), using technology with high autonomy may lead to feelings of uncertainty or ambiguity and in turn to more negative reactions towards a technology. Uncertainty might be more elevated when it is not clear how task stages were processed by the system but the user has to implement actions. This contrast between high autonomy being beneficial to information load while still increasing technostress has to be emphasized when developing and implementing technological tools at context. Objective benefits of a system may not always be related to subjective perceptions and employee outcomes, such as increased technology demands (see e.g. Day et al., 2010, 2012).

Derived from theoretical assumptions of the TAM (Venkatesh & Bala, 2008) we further argued (Hypothesis 3), that participants would be more inclined to set the ***intention of using the DSS*** when the system is designed with low autonomy. This was confirmed in both studies. Again, in study 1, users rated LOA 3 the least positive, indicating a low intention to use the system. These results are in line with the theoretical assumptions proposed by Norman (1994), who proposes that in order fro users to accept a DSS, a system should not be fully autonomous in order to retain a certain degree of user control. However, the present results also indicate, that the effect is not merely due to the degree of task sharing between user and system but also the types of task stages that are being shared. These reactions may be related to the way job roles change when decision-making power is delegated to the system. While not having the autonomy to choose the course of action, users' tasks are reduced to monitoring actions of the system and screening for potential errors. This change of job roles may be central to how users react to a specific system.

We further assumed that different types of experience, that is ***technology*** (Hypothesis 4) and ***job experience*** (Hypothesis 5) impact the relationship between autonomy and user reactions. Literature shows that one reason why individuals develop technostress is the gap between technologies' capabilities and individuals' knowledge concerning the technologies' actions (Ragu-Nathan et al., 2008). In the present studies, only job experience appeared to be a moderator of the relationship between autonomy and user reactions. Regarding technology experience, while being a significant predictor of technostress and user intentions, no significant interaction effects were found. These results may be due to the broad measure of technology experience used in this study. While user reactions were measured with regards to the described DSS, technology experience was measured on a general level, not distinguishing between different types of technologies.

We initially assumed that the experience individuals acquire while working in a position helps to decrease feelings of insecurity when being faced with ambiguous work situations (e.g. the implementation of a new, autonomous technology). Although interaction effects were found for all dependent variables, effect sizes were small. Nevertheless, these results could indicate that when more task processing stages are delegated to a system (i.e. high autonomy) job experience will play a more important role with regards to information load and user intention. This is in line with previous findings, which suggest that users with a high level of job experience are more likely to trust and rely on highly autonomous systems (e.g. Manzey et al., 2009; Ulfert & Scherer, 2020). At the same time, results indicate that concerning affective reactions (i. e. technostress), job experience could play an important role, even when autonomy is low. Although in this study job experience was experimentally varied as part of the vignette scenarios, results could indicate that when autonomy is high, employees will experience similar levels of technostress, regardless of their job experience.

In the experimental setup, ***two different types of DSS*** were described. Study 1 focused on a system completing multiple, interdependent tasks, whereas study 2 focused on a DSS that only completes a single type of task. While it is difficult to directly compare the results of the two studies, the different DSS could have further influenced user reactions. For example, in study 2, mean ratings of user intention were generally lower, compared to study 1, across all levels of autonomy. Similarly, ratings of information load reduction were slightly higher in study 1. These differences may be related to different perceptions of the DSS usefulness, consequently impacting users' intentions (see e.g. Venkatesh & Bala, 2008). Potentially, delegating many tasks to a DSS may initially be perceived as highly useful. However, it is unclear if this perception persists after extended DSS use or if these differences were due to the study's setup. Further exploration will be necessary to understand how employees perceive systems with varying capabilities and how user reactions develop over continued use.

The present study offers first insights into how individuals perceive DSS within the work context. Highly autonomous systems can be used to decrease individuals' information load. However, it is not only the degree to which tasks are shared between user and system that defines users' perception of the DSS. Rather it is the type of task stages that are being processed by the user or the system that impact user reactions. We found that especially when the course of action was selected by the system (task stage: decision making), user reactions were less positive. For example, in study 1, participants rated user intention to be higher, when the system would take over the complete process compared to users implementing courses of actions that are suggested by the system. It can be argued, that users experience a loss of control, whenever decisions are performed by the system rather than the user. Research in the field of DSS similarly reports that users display resistance towards systems when decision-making is delegated to the system (Giboney et al., 2015). In their analysis of reasons for resistance, Jiang et al. (2000) argue that one main reason is uncertainty. Furthermore, they argue, that the level of participation additionally impacts resistance, with low user participation leading to more resistance. In study 1, being unable to decide on the course of actions could have led to individuals expecting to experience more technostress and set lower intention to use such a system. Furthermore, although results concerning experience were only partially supported, they could indicate that when systems are highly autonomous, having a higher level of technology or job experience leads to more positive evaluations of the system.

4.1. Implications for practice

In order for organizations and employees to get the greatest benefit from implementing intelligent DSS in the workplace, it is important to not only consider the objective benefits (e.g. decrease of information load) of such systems. In fact, system characteristics can greatly impact employees' cognitive as well as affective reactions towards such systems. The results of the present study as well as prior DSS research, underline the importance of involving the user (user participation) especially in task processing stages such as decision making, in order to minimize negative reactions or resistance. Partial autonomy may thus be most beneficial for employees, as it may lead to higher performance while avoiding negative user reactions that may be associated with high autonomy systems (see e.g. Endsley, 2016). Employees' experience may positively influence user reactions as technology or job-related skills and knowledge can decrease feelings of ambiguity or uncertainty (e.g. Jiang et al., 2000). Training of technological and job skills could positively influence employees' overall perception of and reactions towards DSS and technology in general. As individuals become more familiar with the use of technologies at work, this could also decrease uncertainties when interacting with intelligent systems and therewith increase perceptions of usefulness.

4.2. Limitations and future research

Despite the promising results of the presented studies, some critical remarks have to be made to optimize future studies. Limitations of the study lie in its applied method of vignette technique as well as the measures.

Firstly, despite vignettes being an economical method, vignette scenarios can only serve as a representation of a fictional scenario (Aguinis & Bradley, 2014; Karren & Barringer, 2002) and thus restricting ecological validity. Even though, results of the pretests and the manipulation checks confirmed that participants correctly understood the task, measured reactions towards the DSS are highly subjective and not necessarily representative of a realistic work setting that comes with various stressors and environmental influences. Thus, the effects of this implementation on external validity and generalizability of results have to be taken into consideration when interpreting results (Aguinis & Bradley, 2014). With little previous research on how users react to different levels of autonomy, the goal of this study was to generate first evidence concerning the role of autonomy in a controlled environment. Therefore, the vignette technique proved to be an appropriate method for addressing this research question. Future studies should further address the role of autonomy in more realistic scenarios, such as interacting with DSS in a laboratory experiment, or in field studies. However, as long as intelligent DSS are not commonly used in the workplace, we recommend focusing on replicating the results of the present study in laboratory experiments to gain a better understanding of the role of autonomy on users' cognitive, affective, and behavioral reactions towards DSS. For instance, laboratory studies could focus on studying how user reactions develop over time and whether negative reactions decrease as users get more used to using the DSS. Such a design helps to avoid sequence effects and allows to study the effects in a longitudinal rather than a cross-sectional design. This further allows to study the relationships between the dependent variables of this study (information load, technostress, user intention) in more detail, to gain an understanding of how, for example, technostress impacts user intentions. Thus, future studies should further refine the proposed research model by including the significant relationships between the different user outcomes.

Secondly, there are limitations regarding the measure of expertise and technostress used in this study which may have influenced the results. In study 1, we used a general 1-item self-rating measure of technology experience. At the same time, participants were asked to rate their reactions towards a very specific DSS, therewith creating a contrast in the levels of generality of the measures. Future studies should thus address general as well as specific technology experience and consider changes of expertise levels over time. Additionally, related measures such as general technology affinity, computer literacy, or computer self-efficacy, should also be included and differentiated from technology experience. Measures of personality (e.g. openness) could further explain differences in prior experience and user reactions. This will enable a better understanding of whether it is more specific or general aspects that impact DSS interaction. Based on prior research, it may be assumed that individuals with high computer self-efficacy and computer literacy will also be more likely to rate the use of DSS positively, develop less technostress, and be more willing to use DSSs at work (Eastin & LaRose, 2000). However, how these constructs independently impact user reactions is still unclear. Future studies should particularly aim to get a better understanding of how individual-level factors, such as specific as well as more generalized experiences and competences, impact user reactions and develop measures to assist employees to adapt better to technologies used in their work environment. With respect to the measure of technostress, results must be interpreted with caution. Although the study offered interesting results, participants were asked to imagine interacting with a DSS, which, most likely, did not result in participants experiencing technostress. In real-life interaction scenarios, interacting with an actual DSS may lead to users experiencing some degree of technostress, resulting in different or more pronounced results. We would therefore like to highlight, that this study focused on participants' subjective rating of expected technostress. This subjective rating may be more closely related to the overall perception of the DSS's characteristics, its usefulness, and ease of use. Therefore, in order to fully understand the relationship between DSS autonomy and technostress, further research will be required which monitors technostress while users interact with DSS (e.g. in experiments). Longitudinal studies will be required to investigate long-term effects on the experience of strain and stress.

Additionally, future studies should further address cultural, team, and organizational level factors as suggested in previous studies (e.g. Lee & See, 2004) as well as relationships between the different user outcomes. Emerging technologies are rapidly changing today's work environment. Therefore, it is more important than ever to understand why employees may experience negative user outcomes and how we can assist them by including these insights into technology and work design processes.

4.3. Conclusion

Overall, the present paper offers a first glimpse into employees' reactions when delegating information processing tasks to intelligent DSS and how these reactions change when agency between the user and the system shifts. We particularly highlighted the importance of autonomy and its effects on cognitive, affective, and behavioral user reactions. In conclusion, it can be argued, that for decreasing individual information load, different types of DSS can serve as a helpful tool, especially when DSS are designed to take over many task processing stages. However, this is also dependent on the types of task stages that are being delegated and may come with negative user reactions such as high technostress or low user intentions.

In the development of user-centered DSS that support employees, the balance between autonomy, the type of delegated task stages, and user reactions poses challenges. By intensively studying measures to further reduce feelings of ambiguity and increase users' feelings of control and participation, DSS pose a unique opportunity for efficiently and effectively decreasing individuals' information load at work. In order to do so, it is crucial to find ways to make users comfortable with sharing tasks with autonomous systems, such as DSS. Based on the results of our study it may be derived, that by increasing employees' technology and job experience, feelings of insecurity or ambiguity could be decreased, and therewith negative user reactions. This could, for instance, be done by enabling and encouraging individuals to increasingly work with DSS and offer training to gain positive experiences with these systems. At the same time, designers of technological systems should take these individual differences into account and develop DSS that are human-centered. The present study offers starting points for developing user-centered DSS that support users in information processing tasks at work.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2021.106987.

Credit author statement

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References

Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational Research Methods, 17*(4), 351–371. https://doi.org/10.1177/1094428114547952

Aiman-Smith, L., Scullen, S. E., & Barr, S. H. (2002). Conducting studies of decision making in organizational contexts: A tutorial for policy-capturing and other regression-based techniques. *Organizational Research Methods, 5*(4), 388–414. https://doi.org/10.1177/109442802237117

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl, & J. Beckman (Eds.), *Action control: From cognition to behavior* (pp. 11–39). Springer.

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology, 32*(4), 665–683. https://doi.org/10.1111/j.1559-1816.2002.tb00236.x

Arnold, V., Collier, P. A., Leech, S. A., & Sutton, S. G. (2004). Impact of intelligent decision aids on expert and novice decision-makers ' judgments. *Accounting and Finance, 44*(1), 1–26. https://doi.org/10.1111/j.1467-629x.2004.00099.x

Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. *MIS Quarterly, 35*(4), 831–858. https://doi.org/10.2307/41409963

Bainbridge, L. (1983). Ironies of automation. In *Analysis, design and evaluation of man–machine systems* (pp. 129–135). Elsevier.

Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of Managerial Psychology, 22*(3), 309–328. https://doi.org/10.1108/02683940710733115

Balfe, N., Sharples, S., & Wilson, J. R. (2015). Impact of automation: Measurement of performance, workload and behaviour in a complex control environment. *Applied Ergonomics, 47*, 52–64. https://doi.org/10.1016/j.apergo.2014.08.002

Balfe, N., Wilson, J. R., Sharples, S., & Clarke, T. (2012). Development of design principles for automated systems in transport control. *Ergonomics, 55*(1), 37–54. https://doi.org/10.1080/00140139.2011.636456

Bates, D., Maechler, M., & Bolker, B. (2012). *lme4: Linear mixed-effects models using S4 classes*. Vienna: R package version 0.999999-0. .

Beaudry, A., & Pinsonneault, A. (2005). Understanding user responses to information technology: A coping model of user adaptation. *MIS Quarterly, 29*(3), 493–524. https://doi.org/10.2307/25148693

Beier, G., Spiekermann, S., & Rothensee, M. (2006). Die akzeptanz zukünftiger ubiquitous computing anwendungen. In A. M. Heinecke, & H. Paul (Eds.), *Mensch & Computer 2006: Mensch und Computer im Strukturwandel* (pp. 145–154) (Oldenbourg).

Brod, C. (1984). *Technostress: The human cost of the computer revolution*. Addison Wesley Publishing Company.

Cascio, W. F., & Montealegre, R. (2016). How technology is changing work and organizations. *Annual Review of Organizational Psychology and Organizational Behavior, 3*, 349–375. https://doi.org/10.1146/annurev-orgpsych-041015-062352

Chase, W. G., & Ericsson, K. A. (1981). Skilled memory. In J. R. Anderson (Ed.), *Cognitive skills and their acquisition* (pp. 141–189). Erlbaum.

Chavaillaz, A., Schwaninger, A., Michel, S., & Sauer, J. (2019). Expertise, automation and trust in X-ray screening of cabin baggage. *Frontiers in Psychology, 10*(256), 1–11. https://doi.org/10.3389/fpsyg.2019.00256

Chi, M. T. H. (2006). Two approaches to the study of experts' characteristics. In K. A. Ericsson, N. Charness, P. J. Feltovich, & R. R. Hoffmann (Eds.), *The Cambridge handbook of expertise and expert performance* (pp. 21–30). University Press.

Day, A., Paquet, S., Scott, N., & 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), 473–491. https://doi.org/10.1037/a0029837

Day, A., Scott, N., & Kelloway, E. K. (2010). Information and communication technology: Implications for job stress and employee well-being. In *New developments in theoretical and conceptual approaches to job stress*. Emerald Group Publishing Limited.

Dwyer, D. J., & Ganster, D. C. (1991). The effects of job demands and control on employee attendance and satisfaction. *Journal of Organizational Behavior, 12*(7), 595–608. https://doi.org/10.1002/job.4030120704

Eastin, M. S., & LaRose, R. (2000). Internet self-efficacy and the psychology of the digital divide. *Journal of Computer-Mediated Communication, 6*(1), JCMC611. https://doi.org/10.1111/j.1083-6101.2000.tb00110.x

Endsley, M. R. (2016). *Designing for situation awareness: An approach to user-centered design*. CRC press.

Endsley, M. R. (2017). From here to autonomy: Lessons learned from human–automation research. *Human Factors, 59*(1), 5–27. https://doi.org/10.1177/0018720816681350

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, mis, and related disciplines. *The Information Society: International Journal, 20*(5), 325–344. https://doi.org/10.1007/978-3-8349-9772-2_15

Eymann, T. (2013). *Digitale Geschäftsagenten: Softwareagenten im Einsatz*. Springer-Verlag.

Flemisch, F., Heesen, M., Hesse, T., Kelsch, J., Schieben, A., & Beller, J. (2012). Towards a dynamic balance between humans and automation: Authority, ability, responsibility and control in shared and cooperative control situations. *Cognition, Technology & Work, 14*(1), 3–18. https://doi.org/10.1007/s10111-011-0191-6

Gao, S., & Xu, D. (2009). Conceptual modeling and development of an intelligent agent-assisted decision support system for anti-money laundering. *Expert Systems with Applications, 36*(2), 1493–1504. https://doi.org/10.1016/j.eswa.2007.11.059

Giboney, J. S., Brown, S. A., Lowry, P. B., & Nunamaker, J. F., Jr. (2015). User acceptance of knowledge-based system recommendations: Explanations, arguments, and fit. *Decision Support Systems, 72*, 1–10. https://doi.org/10.1016/j.dss.2015.02.005

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *The Academy of Management Annals, 14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Goddard, K., Roudsari, A., & Wyatt, J. C. (2012). Automation bias : A systematic review of frequency , effect mediators , and mitigators. *Journal of the American Medical Informatics Association, 1*(19), 121–127. https://doi.org/10.1136/amiajnl-2011-000089

Gruber, H. (2007). Bedingungen von Expertise. In K. A. Heller, & A. Ziegler (Eds.), *Begabt sein in deutschland* (pp. 93–112). LIT Verlag.

Hair, M., Renaud, K. V., & Ramsay, J. (2007). The influence of self-esteem and locus of control on perceived email-related stress. *Computers in Human Behavior, 23*(6), 2791–2803. https://doi.org/10.1016/j.chb.2006.05.005

Hancock, P. A. (2013). In search of vigilance: The problem of iatrogenically created psychological phenomena. *American Psychologist, 68*(2), 97–109. https://doi.org/10.1037/a0030214

Howard, J. (2019). Artificial intelligence: Implications for the future of work. *American Journal of Industrial Medicine, 62*(11), 917–926. https://doi.org/10.1002/ajim.23037

Jiang, J. J., Muhanna, W. A., & Klein, G. (2000). User resistance and strategies for promoting acceptance across system types. *Information & Management, 37*(1), 25–36. https://doi.org/10.1016/S0378-7206(99)00032-4

Kaber, D. B., & Endsley, M. R. (1997). Out-of-the-loop performance problems and the use of intermediate levels of automation for improved control system functioning and safety. *Process Safety Progress, 16*(3), 126–131. https://doi.org/10.1002/prs.680160304

Kaber, D. B., & Endsley, M. R. (2004). The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task. *Theoretical Issues in Ergonomics Science, 5*(2), 113–153. https://doi.org/10.1080/1463922021000054335

Karren, R. J., & Barringer, M. W. (2002). A review and analysis of the policy-capturing methodology in organizational research: Guidelines for research and practice. *Organizational Research Methods, 5*(4), 337–361. https://doi.org/10.1177/109442802237115

Kristof-Brown, A. L., Jansen, K. J., & Colbert, A. E. (2002). A policy-capturing study of the simultaneous effects of fit with jobs, groups, and organizations. *Journal of Applied Psychology, 87*(5), 985–993. https://doi.org/10.1037/0021-9010.87.5.985

Kruijff, G.-J. M. (2012). How could we model cohesiveness in team social fabric in human-robot teams performing under stress?. In *AAAI spring symposium: AI, the fundamental social aggregation challenge*.

Larson, L., & DeChurch, L. (2020). Leading teams in the digital age: Four perspectives on technology and what they mean for leading teams. *The Leadership Quarterly, 31*(1). https://doi.org/10.1016/j.leaqua.2019.101377. Article 101377.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors, 46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392

Lindquist, C. A., & Whitehead, J. T. (1986). Burnout, job stress and job satisfaction among southern correctional officers: Perceptions and causal factors. *Journal of Offender Counseling, Services and Rehabilitation, 10*(4), 5–26. https://doi.org/10.1300/J264v10n04_02

Lyons, J. B., & Havig, P. R. (2014). Transparency in a human-machine context: Approaches for fostering shared awareness/intent. *Lecture Notes in Computer Science, 8525*, 181–190. https://doi.org/10.1007/978-3-319-07458-0_18. LNCS(PART 1).

Madhavan, P., Wiegmann, D. A., & Lacson, F. C. (2006). Automation failures on tasks easily performed by operators undermine trust in automated aids. *Human Factors, 48*(2), 241–256. https://doi.org/10.1518/001872006777724408

Manzey, D., Röttger, S., Bahner-Heyne, E. J., Schulze-Kissing, D., Dietz, A., Meixensberger, J., & Strauss, G. (2009). Image-guided navigation: The surgeon's perspective on performance consequences and human factors issues. *International Journal of Medical Robotics and Computer Assisted Surgery, 5*(3), 297–308. https://doi.org/10.1002/rcs

Mitchell, T., & Brynjolfsson, E. (2017). Track how technology is transforming work. *Nature News, 544*(7650), 290–292.

Moore, J. E. (2000). *One road to turnover: An examination of work exhaustion in technology professionals*. MISQ. https://doi.org/10.2307/3250982

Morgan, R. D., Van Haveren, R. A., & Pearson, C. A. (2002). Correctional officer burnout: Further analyses. *Criminal Justice and Behavior, 29*(2), 144–160. https://doi.org/10.1177/0093854802029002002

Norman, D. A. (1994). How might people interact with agents. *Communications of the ACM, 37*(7), 68–71. https://doi.org/10.1145/176789.176796

Nwana, H. S. (1996). Software agents: An overview. *The Knowledge Engineering Review, 11*(3), 205–244. https://doi.org/10.1017/S026988890000789X

O'Neill, T., McNeese, N., Barron, A., & Schelble, B. (October 2020). Human–autonomy teaming: A review and analysis of the empirical literature. *Human Factors*. https://doi.org/10.1177/0018720820960865

Onnasch, L., Wickens, C. D., Li, H., & Manzey, D. (2014). Human performance consequences of stages and levels of automation: An integrated meta-analysis. *Human Factors, 56*(3), 476–488. https://doi.org/10.1177/0018720813501549

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 39*(2), 230–253. https://doi.org/10.1518/001872097778543886

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 30*(3), 286–297. https://doi.org/10.1109/3468.844354

Parker, S. K., & Grote, G. (2020). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology*, 1–45. https://doi.org/10.1111/apps.12241, 0(0).

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and validation. *Information Systems Research, 19*(4), 417–433. https://doi.org/10.1287/isre.1070.0165

Rasch, B., Friese, M., Hofmann, W., & Naumann, E. (2006). *Quantitative methoden 1*. Springer.

Reinders, M. J., Frambach, R., & Kleijnen, M. (2015). Mandatory use of technology-based self-service: Does expertise help or hurt? *European Journal of Marketing, 49*(1/2), 190–211. https://doi.org/10.1108/EJM-12-2012-0735

Riedl, R., Kindermann, H., Auinger, A., & Javor, A. (2012). Technostress from a neurobiological perspective: System breakdown increases the stress hormone cortisol in computer users. *Business and Information Systems Engineering, 4*(2), 61–69. https://doi.org/10.1007/s12599-012-0207-7

Rossi, P. H., & Nock, S. L. (1982). *Measuring social judgments: The factorial survey approach*. Incorporated: SAGE Publications.

Rotundo, M., & Sackett, P. R. (2002). The relative importance of task, citizenship, and counterproductive performance to global ratings of job performance: A policy-capturing approach. *Journal of Applied Psychology, 87*(1), 66–80. https://doi.org/10.1037/0021-9010.87.1.66

Russell, S., & Norvig, P. (2009). *Artificial intelligence: A modern approach* (3rd ed.). Prentice Hall Press.

Schultz, U., & Vandenbosch, B. (1998). Information overload in a groupware environment: Now you see it, now you don't. *Journal of Organizational Computing & Electronic Commerce, 8*(2), 127–148. https://doi.org/10.1207/s15327744joce0802

Shamir, B., & Drory, A. (1982). Occupational tedium among prison officers. *Criminal Justice and Behavior, 9*(1), 79–99. https://doi.org/10.1177/0093854882009001006

Sheridan, T. B. (2019). Extending three existing models to analysis of trust in automation: Signal detection, statistical parameter estimation, and model-based control. *Human Factors, 61*(7), 1162–1170. https://doi.org/10.1177/0018720819829951

Sheridan, T. B., & Verplank, W. L. (1978). *Human and computer control of undersea teleoperators*. Massachusetts Inst of Tech Cambridge Man-Machine Systems Lab.

Shu, Q., Tu, Q., & Wang, K. (2011). The impact of computer self-efficacy and technology dependence on computer-related technostress: A social cognitive theory perspective. *International Journal of Human-Computer Interaction, 27*(10), 923–939. https://doi.org/10.1080/10447318.2011.555313

Sprague, R. H., & Watson, H. J. (1986). *Decision support systems: Putting theory into practice*. Englewood Cliffs, NJ: Prentice-Hall.

Tan, T. Y., Zhang, L., & Jiang, M. (2016). An intelligent decision support system for skin cancer detection from dermoscopic images. In *2016 12th international conference on natural computation, fuzzy systems and knowledge discovery* (pp. 2194–2199). ICNC-FSKD).

Tarafdar, M., Tu, Q., Ragu-Nathan, T. S., & Ragu-Nathan, B. S. (2011). Crossing to the dark side: Examining creators, outcomes, and inhibitors of technostress. *Communications of the ACM, 54*(9), 113–120. https://doi.org/10.1080/10447318.2011.555313

Team, R. C. (2013). *R: A language and environment for statistical computing*.

Ulfert, A.-S., Ellwart, T., & Antoni, C. H. (2020). September 2-4). Using autonomous systems at work: Effects of user control on technostress [conference session]. In *European academy of occupational health psychology conference, nicosia, Greece. (Symposium cancelled)*.

Ulfert, A.-S., & Georganta, E. (2020). A model of team trust in human-agent teams. In *Companion publication of the 2020 international conference on multimodal interaction* (pp. 171–176). https://doi.org/10.1145/3395035.3425959

Ulfert, A.-S., & Scherer, S. (2020). An integrative model of expertise when introducing advanced digital systems at work. In *Academy of management proceedings* (Vol. 2020, p. 21442). Briarcliff Manor, NY 10510: Academy of Management, 1.

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research, 11*(4), 342–365. https://doi.org/10.1287/isre.11.4.342.11872

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems, 17*(5), 328–376. https://doi.org/10.1080/1097198X.2010.10856507

Wallander, L. (2009). 25 years of factorial surveys in sociology: A review. *Social Science Research, 38*(3), 505–520. https://doi.org/10.1016/j.ssresearch.2009.03.004

Wang, S., Gao, Y., Hodgkinson, G. P., Rousseau, D. M., & Flood, P. C. (2015). Opening the black box of CSR decision making: A policy-capturing study of charitable donation decisions in China. *Journal of Business Ethics, 128*(3), 665–683. https://doi.org/10.1007/s10551-014-2123-x

Wang, B., Liu, Y., & Parker, S. K. (2020). How does the use of information communication technology affect individuals? A work design perspective. *The*

Academy of Management Annals, 14(2), 695–725. https://doi.org/10.5465/annals.2018.0127

Wooldridge, M., & Jennings, N. R. (1995). Intelligent agents: Theory and practice. *The Knowledge Engineering Review, 10*(2), 115–152. https://doi.org/10.1017/S0269888900008122

Yu, T.-K., Lin, M.-L., & Liao, Y.-K. (2017). Understanding factors influencing information communication technology adoption behavior: The moderators of information literacy and digital skills. *Computers in Human Behavior, 71*, 196–208. https://doi.org/10.1016/j.chb.2017.02.005