

6-30-2022

## Examining Technostress at Different Types of Data Scientists' Workplaces

Nicholas Daniel Derra

*Bayreuth Research Institute for Small and Medium-Sized Enterprises, Bayreuth, Germany, ni-co.derra@web.de*

Christian Regal

*University of Hohenheim, Stuttgart, Germany, christian.regal@uni-hohenheim.de*

Simon Henrik Rath

*Bayreuth Research Institute for Small and Medium-Sized Enterprises, Bayreuth, Germany, simon.rath@bfm-bayreuth.de*

Torsten M. Kühlmann

*Bayreuth Research Institute for Small and Medium-Sized Enterprises, Bayreuth, Germany, torsten.m.kuehlmann@bfm-bayreuth.de*

Follow this and additional works at: <https://aisel.aisnet.org/sjis>

---

### Recommended Citation

Derra, Nicholas Daniel; Regal, Christian; Rath, Simon Henrik; and Kühlmann, Torsten M. (2022) "Examining Technostress at Different Types of Data Scientists' Workplaces," *Scandinavian Journal of Information Systems*: Vol. 34: Iss. 1, Article 3.

Available at: <https://aisel.aisnet.org/sjis/vol34/iss1/3>

This material is brought to you by the AIS Journals at AIS Electronic Library (AISeL). It has been accepted for inclusion in *Scandinavian Journal of Information Systems* by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact [elibrary@aisnet.org](mailto:elibrary@aisnet.org).

---

## Examining Technostress at Different Types of Data Scientists' Workplaces

### Cover Page Footnote

The authors acknowledge the financial support and funding by the German Federal Ministry of Education and Research – BMBF (funding agreement number: 02L16D035 and 02L16D030) for the project PräDiTec – Prävention für gesundes und sicheres Arbeiten mit digitalen Technologien. Further, we would like to thank our student assistant Ivan Kharitonov as well as our former colleague Julia Becker for the support during the preparation of this manuscript.

# Examining Technostress at Different Types of Data Scientists' Workplaces

Nicholas Daniel Derra

Bayreuth Research Institute for Small and Medium-Sized Enterprises, Bayreuth, Germany

*nicholas.derra@einstein1.net*

Christian Regal

University of Hohenheim, Stuttgart, Germany

*christian.regal@uni-hohenheim.de*

Simon Henrik Rath

Bayreuth Research Institute for Small and Medium-Sized Enterprises, Bayreuth, Germany

*simon.rath@bfm-bayreuth.de*

Torsten M. Kühlmann

Bayreuth Research Institute for Small and Medium-Sized Enterprises, Bayreuth, Germany

*torsten.m.kuehlmann@bfm-bayreuth.de*

**Abstract.** Data scientists represent a heterogeneous occupational group that has reached high relevance due to the wide-spread availability of quantitative data generated in the rapid progress of digital transformation. These employees play a crucial role in gaining competitive advantages for companies out of such big data. In this context, employees who frequently analyse data often occupy different job titles and, therefore, are difficult to detect. At the same time, a psychological downside of digitalization, which is called technostress, has risen. However, these issues caused by the use of information and communication technologies are rarely examined in the context of specific occupational groups and workplace attributes. Considering these challenges, this article extends current technostress research by focusing on technostress within the specific job class of data scientists. We classify different types of data scientists' workplaces through performing latent

Accepting editor: Henri Pirkkalainen

class analysis using several workplace attributes within a sample of  $n=486$  German data scientists. Subsequently, we reveal considerable distinctions between these classes regarding the intensity of technostress creators, strains due to ICT use, and job performance. We discuss our empirical findings and deliver theoretical contributions as well as practical implications for both employees and employers and starting points for future research.

*Key words:* technostress, strain, digitalization, workplace, data scientist.

## 1 Introduction

Digitalization has already changed numerous aspects of individuals, economies, and society (Fitzgerald et al., 2013; Gimpel et al., 2018). Disruptions of architectures and environments of workplaces by new technological challenge employees in requiring new capabilities for efficiently handling work tasks (Okkonen et al., 2019; Schwemmler & Wedde, 2012; Timonen & Vuori, 2018). Following the institutionalization of new capabilities among the work force, new digital occupations like information security officers (Botta et al., 2007), software developers (Britto et al., 2018), or data scientists (Murawski & Bick, 2017) emerged or excessively gained in relevance among companies. Along this upheaval, employees are often confronted with situations in which work demands are not met by workers capabilities, needs or resources—yielding a set of reactions which are also generally described as work stress (Dekker & Barling, 2005; Houtman, 2005).

Work stress can be related to time limitations, amount of work, the difficulty of work, empathy required, or even physical skills (Houtman, 2005). Psychological research has already proven different reasons for occurring work stress (see, for example, Hartline & Ferrell, 1996; Thompson et al., 1996). In this context, digitalization has been reported to negatively influence the perceived amount of work stress: this causation can be attributed to increased fear of job loss due to automatization and digitalization (Coldwell, 2019) and decreased barriers to separate the private from work (Cijan et al., 2019; Derks et al., 2014; Jääskeläinen, 2015). Thus, unknown new technologies generally contribute to stress among workers who are not familiar with these technologies (Dima et al., 2021).

Due to the opacity in which the work-related use of information and communication technologies (ICT) induces a specific form of stress, a new form called technostress has been specified (Ayyagari et al., 2011; Ragu-Nathan et al., 2008; Tarafdar et al., 2007; Tarafdar et al., 2010). The concept of technostress has already been introduced during the 1980s as the inability to healthfully handle ICT use (Brod, 1984). Technostress may occur if employees feel unable to successfully adapt or to keep up with the multiple

developments regarding digital technologies due to skills which are no longer required because of new software, an abundance of information, frequent interruptions through numerous communication channels, or the overlap of work and leisure time through continuous availability (Tarafdar et al., 2010). Several studies have also shown that, in general, technostress is related to lower productivity, job satisfaction, and loyalty to the employer as well as negative consequences regarding health outcomes (Ayyagari et al., 2011; Srivastava et al., 2015; Tarafdar et al., 2010; Tarafdar et al., 2011). Hence, there is a particular relevance for both employees and managers and, therefore, a significant importance of further investigating technostress at work.

Besides the upcoming rising topic of technostress, digitalization and the closely related datafication (Lycett, 2013) has emerged specific tasks and responsibilities which have upsurged in the rankings of specifically demanded competences in the past couple of years have revolved around an occupation profile to which we refer to as data scientists. Due to the rapidly increasing number of personal computers and mobile devices, a data abundant business world has emerged—with a strong need for new skills to organize, analyze and present data. With the labour market for data scientists, ranking among the fastest growing occupations until 2030 (U.S. Bureau of Labour Statistics, 2021), data-driven decision-making is gaining in relevance among companies—and managers are changing the battlefield from making data available to effectively handle the data available.

Data science and related tasks are following patterns of digitalization and challenge workers to adapt and grow to the new technologies and possibilities available. *Ceteris paribus*, more technology dependent work flows enter the work routine of employees. Employees with higher a degree of digitalization among their workplace also hold a substantial risk of perceiving stress due to ICT usage (Gimpel et al., 2019). Therefore, negative externalities in relation to technostress like diminished productivity and well-being are expected to materialize in relation to data scientist activities.

Considering psychological research, numerous studies have already dealt with specific occupational groups regarding their respective level of work stress (see, e.g., Grace & van Heuvelen (2019), Rees & Cooper (1992), Travers & Cooper (1993)). Furthermore, it has been shown that various job-related (see, for example, Hambrick et al. (2005), Hartline & Ferrell (1996)) and company-related (see, for example, Dekker & Barling (1995), Thompson et al. (1996)) characteristics are associated with different levels of work stress as well. However, current technostress research neglects this job-related context and particularly focuses on general relationships of technostress constructs (Ayyagari et al., 2011; Ragu-Nathan et al., 2008; Tarafdar et al., 2007; Tarafdar et al.,

2019). Therefore, we argue that a research gap has to be filled regarding occupational-specific analysis of technostress to gain a deeper understanding of stress due to ICT use in an organizational context.

To overcome this deficit, we propose an extension of research by examining technostress in the context of specific job profiles. Thereby, we aim to investigate technostress within the occupational group of data scientists, which has been proven to play a crucial role in gaining competitive advantages for companies in today's business environments (Costa & Santos, 2017; Ismail & Abidin, 2016; Mauro et al., 2018). Hitherto, the present study aims to provide insights into different types of data scientists according to their workplace environment and, further, describe the differences between these groups regarding their perceived technostress. Consequently, this work strives to extend the existing literature by considering the impact of workplace characteristics on technostress in the lights of emerging new occupational profiles within the realm of workplace digitalization. The findings will support managers and decision-makers in firms to identify and classify employees being subject to technostress in positions related to data science. Following the practical implications, specific measures can be taken to address and support staff engaged in data science activities to increase satisfaction, productivity, and loyalty to the respective employer. Regarding the crucial role within the enterprises and the foreseen increase of data scientists in the near future, this paper strives to sensitize for the negative aspects of workplace digitalization and increase awareness for a larger amount of workers being subject to technostress.

To achieve this, our study is structured as follows: first, we outline the theoretical background of technostress and data scientist research. Building on this, we define categories of data scientists' workplaces based on job attributes using a sample of  $n=486$  employees who fulfil data science work tasks. The empirically generated categories are analysed with respect to technostress creators, strains due to ICT use, and job performance. To conclude, we will discuss our results and provide theoretical contributions and practical implications as well as approaches for future research.

## 2 Theoretical background

### 2.1 Technostress

Technostress is a specific type of stress emerging from the use of digital technologies (Tarafdar et al., 2019). While technostress itself is seen as a complex transaction between an individual and her/his environment based on the Transactional Theory of

Stress (Cooper et al., 2001; Lazarus and Folkman, 1984) that can not be measured per se, it is induced by technostress creators that are conditions, related to technology use, being perceived as taxing by an individual (Fischer & Riedl, 2017; Tarafdar et al., 2019). While technostress may emerge in both private life (see, e.g., Tarafdar et al. (2019)) and work-life (see, e.g., Becker et al. (2020), Ragu-Nathan et al. (2008)), contemporary research on technostress mostly centers around technostress creators emerging from work-related IT use. Although there exists a varying understanding of creators of technostress in literature, the five technostress creators from Tarafdar et al. (2007) are widely used who distinguish techno-uncertainty (i.e., employees' confusion created by new developments regarding the technologies), techno-insecurity (i.e., employees' fear of being replaced by other employees with higher knowledge in ICT use or by ICT itself), techno-overload (i.e., employees' requirements to work faster, longer, and even more due to ICT usage), techno-invasion (i.e., blurred boundaries between work-related and private issues and time periods), and techno-complexity (i.e., employees' feelings of having a lack of skills in handling job-related technologies). While literature argue that technostress creators may also have bright sides (including productive challenges, high performance, learning, personal growth, and positive emotions (Benlian, 2020; Califf et al., 2020; Tarafdar et al., 2019)), this paper focuses on the dark side of technostress contributing to negative outcomes mostly referred to as technostress-related strain, defined as an individual's psychological, physical, or behavioural responses to technostress creators (Atanasoff & Venable, 2017). Examples of negative outcomes are a reduced level of job performance (Bakker et al., 2008; Bakker & Demerouti, 2017; Taris, 2006), mental exhaustion (Srivastava et al., 2015), or psychological detachment (Barber et al., 2019; Santuzzi & Barber, 2018). Overall, the extent and intensity of technostress-related strain is influenced by the efforts and success of individuals or organisations mitigating technostress creators (i.e., the effects of technostress inhibiting or facilitation measures or aspects) (Salo et al., 2022).

Technological environment conditions, such as the design and features of a certain IT, are antecedents of technostress influencing the extent to which technostress creators arise (Ayyagari et al., 2011; Tarafdar et al., 2019). Currently, literature distinguishes ten technology characteristics, describing abstract capabilities of IT that responsible for the emerge of technostress creators (Becker et al., 2020). Usefulness describes the extent to which the technological features contribute to increasing job performance. If technologies can be learned and used without major effort, they are marked as simple to use. If a technology and its capabilities are stable and therefore free of errors or crashes, then it may be described as reliable. The anonymity of a technology reflects the degree

to which its use is traceable. The reachability of technologies enables communication between users and third parties. In addition, the pace of change of technologies indicates the extent of change to which they are affected. Furthermore, mobility describes whether the technology can also be used on a mobile basis, i.e., outside the designated workplace, or only on a stationary basis. Pull characteristics of technologies mean that information or notifications must be actively retrieved by the user during use, while technologies with push characteristics retrieve and display information independently. Finally, the intangibility of results is a measure of whether the work results created with a technology are physically present or merely available in digital form.

The relationships between technology characteristics, stressors due to ICT usage, technostress inhibitors/facilitators, and strains due to the use of ICT as well as job performance are depicted in Figure 1.

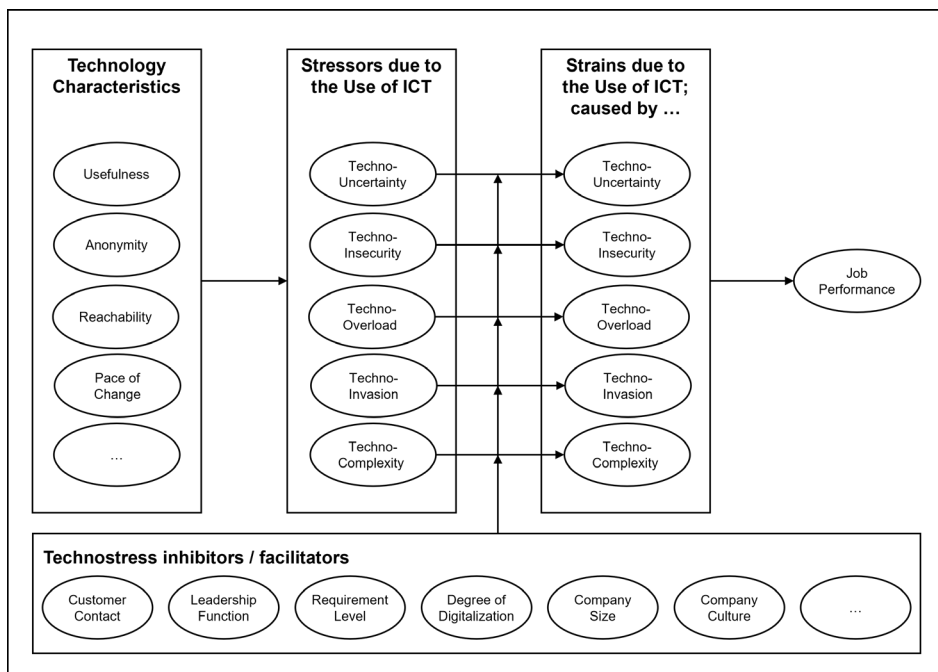


Figure 1. The relationships between technostress creators, strains due to the use of ICT, and job performance (adapted from Ayyagari et al. (2011), Galluch et al. (2015), and Tarafdar et al. (2019))



In the past, studies that dealt with technostress have focused on the relationships between these established constructs in general (Ayyagari et al., 2011; Fischer & Riedl, 2020; Ragu-Nathan et al., 2008; Tarafdar et al., 2007; Tarafdar et al., 2010; Tarafdar et al., 2011; Tarafdar et al., 2015). It is worth noting that also workplace characteristics have been found to be related to (techno)stress and are relevant in terms of inhibiting or facilitating technostress: work stress is therefore associated with jobs that exhibit customer contact (Hartline & Ferrell, 1996) or a leadership function (Ganster, 2005; Hambrick et al., 2005). Furthermore, Golubic et al. (2009) have provided empirical evidence that lower educational background is related to higher work stress levels. Considering company-related characteristics, work stress is also related to the company size (Dekker & Barling, 1995; van Dijkhuizen & Reiche, 1980) and different dimensions of organisational culture within a company (Lansisalmi et al., 2000; Thompson et al., 1996). More specifically, higher levels of work stress are associated with large enterprises (Dekker & Barling, 1995), less perceived support culture (Dekker & Barling, 1995), and greater bureaucracy (Chan et al., 2000). Although the emergence of technostress creators is influenced by technologies (and their associated characteristics) used to pursue job-related tasks and present work-related conditions, little is known about technostress in the context of occupational groups.

In this context, Scaramuzzino & Barfoed (2021) investigated which factors influence the emergence of technostress among Swedish social workers. For example, more than a third of the surveyed workers experience technostress often or very often, especially with regard to techno-invasion. Stadin et al. (2021) did not examine occupational groups, but rather the influence of position on the emergence of technostress. Accordingly, managers exhibit a higher prevalence of technostress than non-managers. With regard to frontline service employees, Christ-Brendemühl & Schaarschmidt (2020) found that they are particularly affected by techno-overload. But there are also occupational groups that are less affected by technostress: Murgu (2021) found that librarians are not prone for technostress. Interestingly, none of the analysed occupational groups or job profiles use highly sophisticated technologies that have become highly relevant in today's businesses.

Due to their importance for modern enterprises and their highly digitalized workplaces, we consider the occupational group of data scientists suitable for examining technostress. For example, data scientists use technologies comprising characteristics that are prone for technostress (see, e.g., technologies with low level of simplicity and reliability (Becker et al., 2020)), while a recent study by Vaast & Pinsonneault (2021) emphasizes that particularly data scientists use technologies that on the one hand en-

able their work but on the other hand also offer the potential of rendering their jobs obsolete.

Hence, we aim to determine whether different classes of data scientists' workplaces differ in terms of technostress creators, technostress-related strains, and overall job performance in order to gain a deeper understanding for the construct of technostress, referring to the necessity of adapting the consideration of specific occupational groups from general work stress literature.

## 2.2 Data scientists

Overall, various studies have already confirmed the importance of data-driven managerial decision-making (Ferraris et al., 2019; Müller et al., 2018; Wamba et al., 2017), showing that big data analytics increase the performance of organisations and, thus, build competitive advantages. Employees who are able to efficiently handle and create knowledge out of data have reached particular relevance through the increased availability, compilation, and storage of large amounts of data provided by the digital transformation of businesses, leading to a great demand for these employees (Davenport, 2020; Ismail & Abidin, 2016; Mauro et al., 2018). Though, it has been challenging to pinpoint tasks and responsibilities of these so-called data scientists: researchers have explored job profiles (Costa & Santos, 2017), educational curricula (Richards & Marrone, 2014), or gathered key insights from experts (Mikalef et al., 2018; Stanton & Stanton, 2016) to identify a data scientist's required skills and knowledge.

Regarding the occupational dimension of skill variety proposed by Hackman & Oldham (1976), the data scientist's job is associated with a wide variety of required skills and knowledge domains. In this context, analytical and statistical skills are particularly relevant (Costa & Santos, 2017; Doyle, 2019; Ismail & Abidin, 2016; Richards & Marrone, 2014). Following this skill variety, analyses of occupational profiles have shown that under the single term 'data scientist', many different occupational roles have been developed in business practice, e.g., business analysts, data engineers, statisticians, and data analysts (Baškarada & Koronios, 2017; Ho et al., 2019; Mauro et al., 2018). This variety of roles exists due to the heterogeneous application domains, organisational structures, and purposes of data processing. Therefore, a data scientist's job can be regarded as more of an umbrella term comprising heterogeneous tasks and requirements (Doyle, 2019; Mauro et al., 2018).

Considering this variety of tasks and requirements, research has summarized that a person fulfilling all the requirements of a data scientist can hardly be found in the

labour market—rendering the person a “Unicorn Data Scientist” (Baškarada & Koronios, 2017; Davenport, 2020; Davenport & Patil, 2012). Therefore, defining a data scientist as an expert who extracts knowledge from collected data as well as manages the whole data lifecycle and regarded IT infrastructures as proposed by Manieri et al. (2015) seems to be unrealistic in the context of real company environments, particularly due to the necessity of specific domain knowledge. Furthermore, recent studies focus on examining data scientists' tasks and roles but, at the same time, little is known about the workplace environments of data scientists.

In addition, employees who fulfil some of a data scientist's tasks are also hard to find within a company. The tasks of efficiently analysing data are spread among several employees with various job titles since large datasets occur in most departments of a company (Janssen et al., 2017) and, moreover, due to the necessity of exhibiting broad domain knowledge for efficiently performing data science (Waller & Fawcett, 2013). Consequently, these employees do not work at the analysis of data full-time and do not hold related occupational titles, but, at the same time, their job descriptions require data science skills and they frequently fulfil data science tasks. Hence, employees who frequently work as part-time data scientists can not be detected through classifications based on job titles but have to be identified by their tasks. Nevertheless, for enhancing data scientists' performance by tackling technostress, it is crucial to detect employees who frequently fulfil data scientist tasks.

In this context, considering the job description for data scientists proposed by the German Federal Employment Agency (2020), data scientists do screen work, comprising both customer interaction and teleworking. Their work is mostly dependent on the usage of numerous ICT: they frequently use a variety of hard- and software including operating systems, the internet, telephone, network systems, information and knowledge management systems, development software, and statistical software. However, almost all of these ICTs are not job-specific since their use is generally common in office workplaces. Yet, the frequent application of statistical software seems to be a well-performing attribute to classify a data scientist's workplace since data science work implicates the analysis of various data. Therefore, we define an employee working as a data scientist not as a person holding specific job titles but based on the everyday use of statistical software programs.

## 3 Methodology

### 3.1 Sample

The data we used for our examination were collected within a large research project examining technostress among German employees and developing preventive measures to efficiently reduce technostress at work. After running a quantitative pre-test containing  $n_{pre} = 445$  participants, the data of the main study with a sample size of  $n_{final} = 4,560$  participants was collected by an external panel provider. The applied questionnaire included numerous control variables to test representativity (age, sex, industry, employment status, number of hours worked per week). Regarding the control variables age, sex, and industry, preliminary analysis showed that the main study sample represents the German workforce (Federal Statistical Office of Germany, 2018a; Federal Statistical Office of Germany, 2018b). The survey was conducted online and participants received an expense allowance of 3.70 USD / 3.10 EUR after completing the questionnaire. Before answering the first question of the survey, participants confirmed they were over 18 years old and have read the information about the research project itself, data processing, and data protection. Participants have further been informed that withdrawal from their approval of participation anytime without any negative consequences.

For identifying data scientists within our sample, we subsampled full-time workers (*number of hours worked per week*  $\geq 35$ ) who utilize statistical software daily. After data cleaning (invalid responses and outliers), the subsample consisted of  $n = 486$  data scientists. Within the sample, the female-male ratio is 32.30% to 67.70% and about 55.14% of the participants possess an academic background (see Table 1).

### 3.2 Measures

The questionnaire was phrased in German. Three German native speakers translated the questions which were originally formulated in English and established a final wording for translating the items. The questions were kept simple, specific, concise, without ambiguous questions, comprehensible for avoiding common method bias (Podsakoff et al., 2003). Since decreasing evaluation apprehension reduces common method bias as well (Podsakoff et al., 2003), participants were further informed that the items could not be answered right or wrong. Finally, the measures were carefully validated with a quantitative pre-test with  $n_{pre} = 445$  external respondents. Besides the construction requirements described above, we additionally performed Harman's single factor test (Harman, 1967) to consider possible common method bias within our data. For this,

## Derra et al.: Examining Technostress at Different Types of Data Scientists' Workplaces

<i>Gender</i>	<i>N</i>	<i>%</i>	<i>Digital Literacy</i>	<i>N</i>	<i>%</i>
Male	329	67.70	Low	74	15.22
Female	157	32.30	High	412	84.78

<i>Age</i>	<i>N</i>	<i>%</i>	<i>Education</i>	<i>N</i>	<i>%</i>
<21	23	4.73	Primary School Education	5	1.03
21-24	112	23.04	Secondary School Education	43	8.85
25-39	147	30.25	High School	60	12.35
40-59	128	26.34	Completed Apprenticeship	110	22.63
60-64	46	9.47	College Degree (Bachelor)	104	21.40
>65	30	6.17	College Degree (Master)	141	29.01
			Dissertation (PhD)	23	4.73

Table 1. Demographic properties of the sample (n=486)

we conducted an unrotated principal component analysis with all items we used for group comparisons (Chang et al., 2010; Podsakoff et al., 2003; Tehseen et al., 2017). Since the highest proportion of variance attributed to one factor was about 17.07%, common method bias is not considered as a problem within the examined data. Additionally, we calculated the VIF in order to check for multicollinearity. The resulting VIFs ranging from 1.09 up to 2.33 are below the widely accepted threshold of 5.0 (Henseler et al., 2015) and, hence, multicollinearity can be considered as not present. Further, Appendix 4 contains descriptive statistics, internal consistency, AVE, and factor loadings for the used constructs.

For our analyses, we subsampled full-time working data scientists who utilize statistical software daily by asking the participants for their contractual weekly working time as well as the usage of statistical and analysis software (e.g., data mining tools) as proposed by Gimpel et al. (2018), using a 5-point rating scale ranging from 0 = *never* to 4 = *several times a day*.

Considering the heterogeneity of data scientists' workplaces, we asked the participants for both job-related and company-related attributes in order to develop a general picture of their respective workplaces. For this, we focused on attributes which have already been proven to be related to employees' stress at work, i.e., customer contact (Hartline & Ferrell, 1996), the required educational level (Golubic et al., 2009) and leadership function (Ganster, 2005; Hambrick et al., 2005) for the job dimension and, further, company size (Dekker & Barling, 1995; van Dijkhuizen & Reiche, 1980) and organisational culture (Chan et al., 2000; Dekker & Barling, 1995; Lansisalmi et al., 2000; Thompson et al., 1996) representing the company dimension. Since the use of ICT at work also represents a highly relevant characteristic in the context of technostress, we added the workplace's degree of digitalization as another job-related attribute.

Customer contact, leadership function, the level of requirement, and company size were asked in a binary format (see Table 2). Following Gimpel et al. (2019), we measured the degree of digitalization via the number of technologies used at work and their frequency of use. In doing so, we asked for the use of 40 widely used technologies (Gimpel et al., 2018), using a 5-point rating scale ranging from 0 = *never* to 4 = *several times a day*. The number and the frequency of technologies at work were then combined to a degree of digitalization, which is classified into four categories through median splits: few technologies rarely used, few technologies frequently used, many technologies rarely used, and many technologies frequently used. For describing organisational culture, we used the organisational culture index with its elements innovativeness, support, and bureaucracy as proposed by (Wallach, 1983) with a 5-point rating scale from 0 = *not at all* to 4 = *entirely*. Median splits transformed the answers into binary categories.

The five technostress creators—techno-uncertainty, techno-insecurity, techno-overload, techno-invasion, and techno-complexity—were assessed by established and validated scales proposed by Ragu-Nathan et al. (2008): techno-uncertainty was measured with four items (e.g., “There are constant changes in computer software in our organisation.”); techno-insecurity is captured by five items (e.g., “I have to constantly update my skills to avoid being replaced.”); techno-overload was measured with four items (e.g., “I am forced by this technology to work with very tight time schedules.”); techno-invasion encompasses 3 items (e.g., “I have to be in touch with my work even during my vacation due to this technology.”); techno-complexity includes five items (e.g., “I need a long time to understand and use new technologies”). All items for measuring technostress creators, strain due to the use of ICT, and job performance, were asked using a 5-point Likert-type rating scale ranging from 0 = *I do not agree at all* to 4 = *I totally agree*. For measuring strain due to ICT use, the participants responded to

<i>Aspect</i>	<i>Indicators</i>	<i>Characteristics</i>
<i>Job</i>	Customer Contact	Yes; No
	Leadership Function	Yes; No
	Requirement Level	Non-academic; Academic
	Degree of Digitalization	Few, Rarely; Few, Often; Many, Rarely; Many, Often
<i>Company</i>	Company Size	less than 250; 250 or more
	Innovative Culture	low; high
	Supportive Culture	low; high
	Bureaucratic Culture	low; high

Table 2. Overview of the measures and their ranges for LCA

the question “And how much does that strain you?” after every item regarding the respective technostress creator, guided by the scales of Ayyagari et al. (2011) who propose the direct measurement of ICT-related strains. For measuring the strain due to the use of ICT, we used a 5-point Likert-type rating scale from 0 = *not at all* to 4 = *very largely*. By that, we measured the overall level of strain due to ICT use and determined the level of strain caused by the respective technostress creator. In addition, job performance was measured by four self-report items regarding work performance as proposed by Chen & Karahanna (2014). The items asked for both fulfilling general workplace demands and success in handling work tasks (e.g., “I have a reputation in this organisation for doing my work very well.”). To check how well the scales perform within our sample, we calculated the factor loadings and checked them according to the 0.4-0.3-0.2 rule, i.e., at least a loading of 0.4 on the main factor, no cross-loadings greater than 0.3, and the difference between main loading and cross-loading is at least 0.2 (Howard, 2015). In reviewing the loadings, we found that for 21 of 24 items, the rule can be successfully applied. For the remaining three items, however, one part of the rule is violated, i.e., the difference between main loading and cross-loading is less than 0.2. Due to the fact that only for a very small part of the items just one part of the rule was violated as well as, in these cases, the cross-loadings are all below 0.3 and, thus, could also be considered irrelevant (Costello & Osborne, 2005), it can be concluded that the used scales are performing well in our sample.

### 3.3 Data analysis

For analysing the data, we utilized the open-source software R (R Development Core Team, 2019) and the R Studio user interface (RStudio Team, 2019). After subsampling the daily-users of statistical software and examining the data through descriptive analysis, we performed a Latent Class Analysis (LCA) using the workplace attributes explained above to identify subgroups of data scientists.

We used the attributes—customer contact, leadership function, required educational level, degree of digitalization, company size, level of innovativeness, level of support, and level of bureaucracy—as indicators and conducted LCAs that specified 2 to 8 classes each while repeating these computations ten-times for robustness. We applied well-established fit measures for evaluating LCA models using log-likelihood-ratio  $G^2$  test for goodness of fit, which has been proven to work better than  $X^2$  test for LCA (Nylund et al., 2007) and both the Akaike Information Criterion AIC (Akaike, 1974) and the Bayesian Information Criterion BIC (Schwarz, 1978) for model comparison. We implemented LCA using the specific R package ‘poLCA’ (Linzer & Lewis, 2011).

After identifying the best latent class model, we compared the discovered classes of data scientists regarding their perceived level of technostress creators, strain due to ICT use, and job performance through running group comparisons. Since descriptive analysis showed that the data is both not normally distributed and contains heterogeneity of variance, we implemented the van der Waerden normal score test (van der Waerden, 1952) since it has proven to deliver superior results compared to both parametric (ANOVA test) and nonparametric (Kruskal-Wallis test) test irrespective of whether the assumptions of normality and homogeneity of variance apply for the samples (Hageman, 1992; Tucker, 1994).

Similar to the Kruskal-Wallis test, the van der Waerden normal score test replaces ranks with so-called normal scores  $W_{i,j}$  which are inverse normal statistics calculated from quantiles within the standard normal distribution through

$$W_{i,j} = \Phi^{-1}\left(\frac{R(X_{i,j})}{N+1}\right)$$

where  $\Phi^{-1}$  denotes the normal quantile function,  $X_{i,j}$  is the  $i$ th value within the  $j$ th group,  $R(X_{i,j})$  is the assigned rank of  $X_{i,j}$ ,  $n_i$  is the size of sample  $i$ , and  $N = \sum n_i$  is the size of all samples combined. The van der Waerden normal score test statistic  $W$  is then defined as

$$W = \frac{(N-1) \sum_{i=1} \frac{(\sum_j W_{i,j})^2}{n_i}}{\sum_{i=1} \sum_{j=1} W_{i,j}^2}$$



with  $W_{ij}$  as the  $j$ th expected normal score in the  $i$ th sample (Feir-Walsh & Toothaker, 1974; van der Waerden, 1952).

We first examined global comparisons for every technostress creator, strain variable, and job performance ( $\alpha = 0.05$ ). If a global test was significant, we further implemented pairwise comparisons with controlling for family-wise error rates via Holm-Bonferroni method (Holm, 1979) for investigating the specific differences between the data scientist workplaces. For investigating the effect sizes, we further considered Vargas and Delaney's A (Vargha & Delaney, 2000).

Since perceived technostress is also related to employees' age (Ragu-Nathan et al., 2008; Şahin & Çoklar, 2009), we further tested for homogeneity of the latent groups regarding age through another van der Waerden normal score test. The result was not significant ( $p = 0.275$ ), so the groups' differences regarding technostress cannot be explained by age differences.

## 4 Results

### 4.1 Latent class analysis

Considering LCA's results regarding data scientists' workplace attributes, we first exclude the model with two classes of workspaces since this model is significant for log-likelihood-ratio  $G^2$  (compare Table 3). Regarding goodness of fit, the model with eight classes achieves the best values. Simultaneously, the model with four classes shows the best (or rather lowest) value for AIC, while the model with three classes performs best for BIC. Thus, these models have to be examined in more detail. Having only a few styles in your unformatted manuscript reduces clutter in the styles pane and simplifies the formatting process.

Given our goal of detecting explainable workplace classes, a split into eight types would separate the sample into sparse groups and, further, seems rather complex, which can be seen at high scores in both AIC and BIC. Therefore, the model with eight groups is rejected. Regarding AIC, the model with four classes is preferred, while model three performs best in BIC, so both models seem to be comparable in balancing fit and complexity. Based on these results, we compare the models' goodness of fit where the model with four classes outperforms regarding log-likelihood-ratio  $G^2$ . Furthermore, considering the sample's distribution among the different types of workplaces within the models, we find a noticeable imbalance through a very dominant type containing more than 50% of the sample within the 3-type model. Hence, we select the model

with four classes. This decision is further supported by the bootstrap likelihood ratio test (BLRT) that is found to be another high-performing statistical fit measure for latent class analysis (Nylund et al. 2007).

<i>n</i>	<i>log-likelihood</i>	<i>G</i> <sup>2</sup>	<i>p</i> ( <i>G</i> <sup>2</sup> )	<i>X</i> <sup>2</sup>	<i>p</i> ( <i>X</i> <sup>2</sup> )	<i>AIC</i>	<i>BIC</i>	<i>p</i> ( <i>BLRT</i> )
2	-2626.427	536.590	0.012	675.376	0.001	5294.854	5382.764	0.001
3	-2578.857	441.149	0.659	500.940	0.063	5221.713	<b>5355.672</b>	0.001
4	-2556.279	395.993	0.947	480.029	0.109	<b>5198.558</b>	5378.565	<b>0.026</b>
5	-2545.930	375.296	0.977	472.970	0.085	5199.860	5425.915	0.270
6	-2537.080	358.023	0.988	459.732	0.094	5204.588	5476.691	0.780
7	-2529.055	340.752	0.992	421.515	0.375	5209.316	5527.468	1.000
8	<b>-2523.295</b>	<b>329.021</b>	<b>0.997</b>	<b>392.895</b>	<b>0.882</b>	5219.586	5583.786	1.000

Table 3. The goodness of fit measures of the LCA for the varying number of assumed classes *n*

Table 4 shows the impact of the indicators' characteristics on the respective association of a data scientist with a type of workplace as well as the distribution of the sample. We consider influences with a probability of  $\geq \frac{2}{3}$  for binary and  $\geq \frac{1}{3}$  for quaternary indicators as a major characteristic.

Considering these results, we are now able to distinguish classes of data scientists' workplaces as follows:

- **Type 1—Customer Service Management within SMEs (CSM-SME):** workplaces that require direct contact to the customer; furthermore, the data scientists working here use only a few ICT but make often use of them; this workplace is particularly common in small and medium-sized companies and does not require academic know-how; employees tend to work in innovative companies with a strong supportive culture but, at the same time, have to deal with high bureaucracy.
- **Type 2—Customer Interaction Lead Position with Low Levels of Innovativeness, Support, and Bureaucracy (CIL-noISB):** workplaces with leadership function that also require customer contact; these workplaces tend

Dimension	Indicators	Characteristic	Latent Class			
			Type 1 (83)	Type 2 (91)	Type 3 (225)	Type 4 (87)
Job	Customer Contact	Yes	<b>0.906</b>	<b>0.857</b>	<b>0.834</b>	0.508
		No	0.094	0.143	0.166	0.492
	Leadership Function	Yes	0.651	<b>0.669</b>	<b>0.906</b>	0.200
		No	0.349	0.332	0.094	<b>0.800</b>
	Requirement Level	Non-academic	<b>0.794</b>	0.380	0.295	0.475
		Academic	0.207	0.620	<b>0.705</b>	0.526
	Degree of Digitalization	Few, Rarely	0.106	0.200	0.070	0.150
		Few, Often	<b>0.586</b>	0.281	0.182	<b>0.660</b>
		Many, Rarely	0.153	<b>0.346</b>	<b>0.421</b>	0.081
		Many, Often	0.155	0.172	0.327	0.110
Company	Company Size	less than 250	<b>0.914</b>	0.614	0.319	0.055
		250 or more	0.087	0.386	<b>0.681</b>	<b>0.945</b>
	Innovativeness	Low	0.209	<b>0.923</b>	0.064	0.342
		high	<b>0.792</b>	0.077	<b>0.936</b>	0.659
	Support	Low	0.167	<b>0.783</b>	0.094	0.526
		high	<b>0.833</b>	0.217	<b>0.906</b>	0.474
	Bureaucracy	Low	0.194	<b>1.000</b>	0.074	0.239
		high	<b>0.806</b>	0.000	<b>0.926</b>	<b>0.761</b>

Table 4. The probabilities that one class holds a specific characteristic; bold values are remarkable for the respective type of workplace compared to the other types

to appear within enterprises exhibiting a low culture of innovation and support as well as bureaucracy; in addition, a broad range of ICT is exploited while the individual technologies are rarely used.

- **Type 3—Customer Interaction Lead Position within Large Enterprises (CIL-LE):** workplaces comprising direct contact with customers which are also associated with both academic background and a leadership position; herein, a large number of ICT is utilized in different frequencies; this workplace type often occurs in large enterprises having a high level of innovative, support, and bureaucratic culture.
- **Type 4—Back Office Expertise within Large Enterprises (BOE-LE):** workplaces that are not associated with management responsibilities; only a few ICT are used here but, at the same time, these technologies are frequently utilized; this type of workplace is particularly common in large companies holding a dominant bureaucratic culture.

Considering the distribution of data scientists in this context, it is notable that the highest percentage of data scientists are assigned to CIL-LE with about 46.3% ( $n_{CIL-LE} = 225$ ) while the other types of workplaces are comparably distributed with 17.0% to 18.70% each (for a detailed view of the respective group structures, see Appendix 3).

## 4.2 Van der Waerden normal score test

We now compare the four types in terms of both technostress creators and strains caused by ICT as well as their perceived job performance. As already pointed out, we explicitly distinguish technostress creators and strain due to ICT use as proposed in technostress literature (Ayyagari et al., 2011; Salanova et al., 2007). Figure 2 shows the results for the five technostress creators and the perceived job performance, while Figure 3 shows the technostress-related strains. The 25%, 50%, and 75% quantiles, as well as mean and standard deviation, are given for the four types of workplaces each in Appendix 5.

Data scientists working at CIL-LE workplaces report the highest values regarding the technostress creators uncertainty, insecurity, overload, and invasion compared to the other classes and, further, the highest cumulated demands regarding the five technostress creators as well ( $mean_{cum} = 1.965$ ). Concerning the remaining facet techno-complexity, data scientists from CIL-noISB workplaces report the highest value.

Regarding technostress-related strains, CIL-LE data scientists only hold the highest values for strains from two technostress creators, namely insecurity and invasion. However, these data scientists generally have the highest strains across all facets in total

## Derra et al.: Examining Technostress at Different Types of Data Scientists' Workplaces

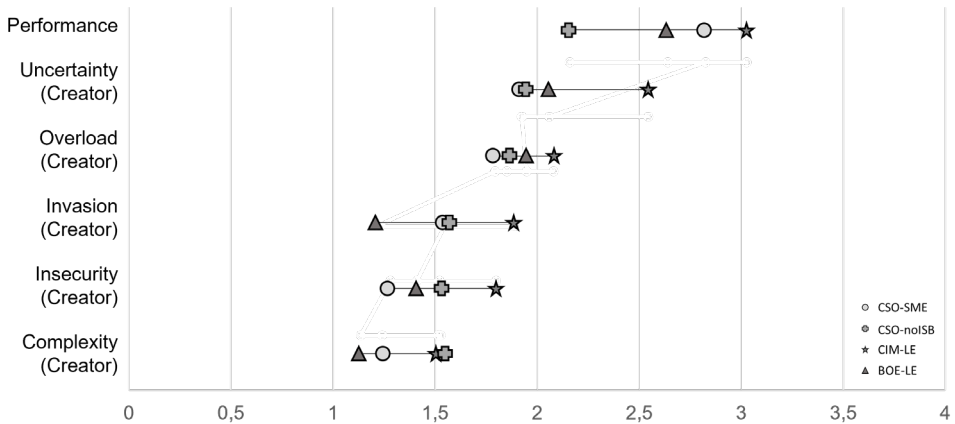


Figure 2. Mean of technostress creators and job performance, for four classes of data scientists' workplaces

( $mean = 1.441$ ). The highest values for both overload- and uncertainty-related strains is now at CIL-noISB-type and no longer for CIL-LE. Furthermore, CIL-noISB occupies the highest value for complexity-related strain, consistent with the respective technostress creator. Interestingly, data scientists report the highest value for CIL-LE workplaces' job performance, despite overall highest values for technostress creators and strains due to digital technologies. In contrast, CIL-noISB report a clearly worse job performance compared to the other classes. Besides these issues, data scientists of the other workplace classes (CSM-SME and BOE-LE) do not show any apparent peculiarities in both technostress creators and strains due to the use of ICT as well as job performance.

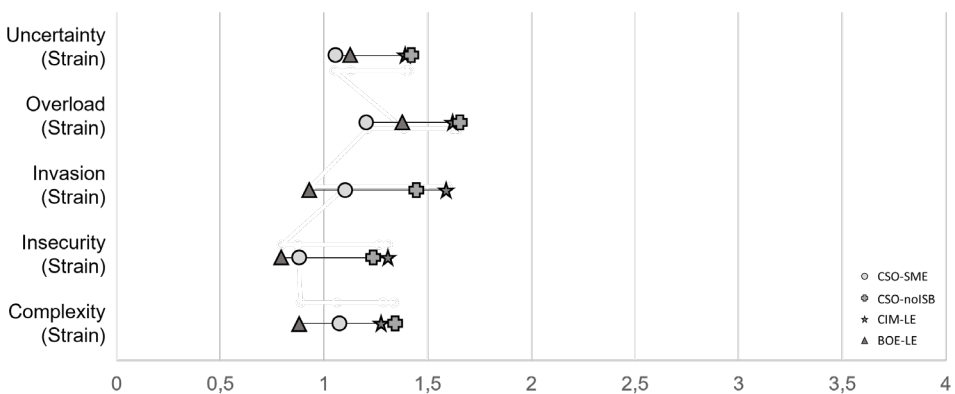


Figure 3. Mean of technostress-related strains, for four classes of data scientists' workplaces

For examining whether the detected types of workplaces differ in their levels of technostress creators and strains, we first conducted global van der Waerden normal score tests on the four classes of workplaces. Table 5 shows the results of these global tests.

<i>Dependent Variable</i>	<i>Technostress Creator</i>	<i>Strain</i>
<i>Techno-Uncertainty</i>	< 0.001	0.036
<i>Techno-Insecurity</i>	0.001	< 0.001
<i>Techno-Overload</i>	0.155	0.020
<i>Techno-Invasion</i>	< 0.001	< 0.001
<i>Techno-Complexity</i>	0.028	0.007
<i>Job Performance</i>	< 0.001	

Table 5. p-values for global van der Waerden normal score tests comparing the workplace classes of data scientists

Considering technostress creators, there are global differences within the subgroups for the factors techno-uncertainty, techno-insecurity, techno-invasion, and techno-complexity. Concerning the technostress-related strains, the results show that at least one class significantly differs from the others at every single technostress creator. Finally, job performance includes significant differences as well.

Subsequently, we use pairwise van der Waerden normal score tests with alpha adjusting by applying the Holm–Bonferroni method (Holm, 1979) to determine which types of workplaces differ significantly. We utilized Vargas and Delaney’s A (Vargha & Delaney, 2000) for investigating the effect sizes. In the following, we focus on reporting significant differences that show at least a moderate effect to meet the call for statistical and practical significance (Mohajeri et al., 2020). For exact values and results from all deducted tests, see Appendix 1 and 2, respectively.

- **Techno-uncertainty:** For techno-uncertainty as a technostress creator, CIL-LE workplaces significantly distinguish from all other types and show explicitly

higher values than all other classes. However, in terms of strain, there are no significant differences between the groups. Although a previously conducted general van der Waerden normal score test detected a significant difference between the workplace types, this difference is no longer identifiable at the level of pairwise comparisons. Thus, there is no significant difference concerning strains due to techno-uncertainty. This phenomenon of a globally significant and non-significant pairwise-test results can be observed when weak significant results (the global test had a p-value of 0.036) are further penalized by the correction procedure and are therefore no longer significant.

- **Techno-insecurity:** Regarding techno-insecurity as a technostress creator, CIL-LE again differs from CIL-SME, although, however, the difference is moderate. In this context, CIL-LE reports higher values. On the other hand, there are several significant differences in strains, e.g., CIL-LE considerably distinguishes from BOE-LE and moderately from CIL-SME, with CIL-LE exhibiting higher values. Likewise, CIL-noISB moderately differs from BOE-LE whereby CIL-noISB reports higher values.
- **Techno-overload:** Techno-overload as a technostress creator does not report any significant differences between the workplace classes. Interestingly, there is a moderate difference in related strain between CSM-SME and CIL-noISB, with CIL-noISB surpassing the other.
- **Techno-invasion:** Considering techno-invasion as a technostress creator, there is a significant variance between CIL-LE and BOE-LE, with CIL-LE reporting clearly higher values. In terms of strain and besides the respective significant difference between CIL-LE and BOE-LE, there are also significant distinctions between CIL-LE and CSM-SME as well as CIL-noISB and BOE-LE. In this context, CIL-LE has moderately higher values than CSM-SME and significantly higher values than BOE-LE. In comparison, BOE-LE reports clearly higher values than CIL-noISB.
- **Techno-complexity:** Although the general van der Waerden normal score test detected a significant deviation between the workplace types in terms of technostress creators, this difference disappears at the level of pairwise comparisons. Thus, there is no significant variance concerning techno-complexity as a technostress creator. In contrast, significant differences regarding strain due

to techno-complexity between BOE and both CIL-noISB and CIL-LE were observed, with BOE-LE reporting moderately smaller values.

- **Job performance:** The differences between the types of data scientists' workplaces regarding job performance show that CIL-LE is distinctly different from both CIL-noISB and BOE-LE holding higher job performances. Furthermore, CIL-noISB also performs significantly worse than workplace CSM-SME and BOE-LE.

To sum up, CIL-LE incumbents highly differ from both CSM-SME incumbents and BOE-LE incumbents reporting higher values for technostress creators and technostress-related strains. At the same time, there are also differences between CIL-noISB incumbents and BOE-LE incumbents in terms of strain due to both techno-invasion and techno-complexity. In contrast, CIL-LE employees report higher values for perceived job performance despite their higher demands in both technostress creators and strain due to ICT use.

## 5 Discussion

In general, data scientists represent a highly digitalized occupational group that is of crucial importance for today's companies to create knowledge and, accordingly, competitive advantages out of big data. In this paper, we contribute to the problems of detecting employees who fulfil data scientists' tasks by (i) providing a definition based on data scientists' ICT use which is closer to businesses' reality compared to other definitions in the context of job titles and (ii) detecting classes of data scientists' workplaces which differ regarding job-related and company-related attributes. In doing so, we found four kinds of workplaces: customer service management within SMEs (CSM-SME), customer interaction lead position with low levels of innovativeness, support, and bureaucracy (CIL-noISB), customer interaction lead position within large enterprises (CIL-LE), and back office expertise within large enterprises (BOE-LE), with CIL-LE being the largest class of data scientists' workplaces. This suggests that data scientists more likely hold lead positions within large enterprises and exhibit customer contact. These findings are clearly against associating data scientists' workplaces with in-house tasks. Therefore, data science expertise should be considered when hiring employees for leadership workplaces since these workplaces often require the fulfilment of data scientist tasks. Further, it is quite surprising that data scientists often report high levels of innovativeness and support along with high bureaucracy (and low levels each,



respectively), which seems to be contradicting. Moreover, it is worth pointing out that data scientists' lead positions are likely to utilize many ICT technologies but use them quite rarely. In contrast, employees without lead responsibilities tend to use relatively few technologies commonly. Thus, leaders have to gain broader knowledge due to the use of ICT.

Subsequently, we contribute to technostress research by adapting the consideration of specific occupational groups as widely used in work stress literature by examining stressors and strains due to ICT usage as well as the overall job performance within the detected classes of data scientists workplaces. By that, we found significant differences between the groups regarding technostress: the groups report different levels of technostress creators as well as related strains and, in particular, vary regarding the composition of technostress' roots (i.e., the technostress creators) and suffering (i.e., the technostress-related strains). The results suggest that data scientists holding leadership positions are higher demanded by ICT developments which may be caused by top-down strategies for launching new technologies. Furthermore, leaders within SMEs seem to be less demanded due to new ICT compared to leaders in large enterprises. Also, it is notable that CIL-LE seem to feel more replaceable than CSM-SME incumbents regarding ICT knowledge, while there is no significant difference compared to BOE-LE incumbents. I.e., the combination of leadership and working within a large enterprise seems to guide data scientists to feel less important for their company in terms of ICT-related knowledge. The results further indicate that the use of many technologies which is highly connected to leadership workplaces generally leads to higher strains in this regard and, moreover, strain due to techno-invasion rather occurs within large companies. Lastly, it is also noteworthy that BOE-LE incumbents report significantly less techno-complexity than both the leadership workplace classes. Hence, the findings lead to the conclusion that data scientists who work as leaders are especially in danger of perceiving technostress creators as well as strain due to the use of ICT and, further, employees within large enterprises are more likely to perceive strain due to techno-invasion.

Overall, CIL-LE incumbents reported the highest levels of both perceived technostress creators and technostress-related strain but, at the same time, assessed themselves with the strongest job performance. Since technostress has been shown to negatively influence job performance (Bakker et al., 2008; Bakker & Demerouti, 2017; Taris, 2006), CIL-LE incumbents seem to overcome this issue more efficiently compared to the other classes of data scientists. In this context, one factor could be that CIL-LE workplaces are highly associated with innovative and supportive culture within the enterprise which may enhance the feeling of being productive and, further, lead to success in performing active coping strategies like seeking social support (Carver et al., 1989).

This suggestion is supported by the fact that CIL-noISB incumbents which represent the other leadership class report the worst job performance: they seem to suffer more from technostress by getting less support in overcoming it.

## 5.1 Theoretical contribution

Considering technostress as an important aspect of health at the workplace both employers and employees have to carefully deal with, we contribute to current technostress research by successfully adapting concepts of work stress research regarding workplace attributes and, further, the examination of an occupational group's specificities to technostress context. More specifically, we provide a job-specific view of technostress considering the highly digitalized and heterogeneous job class of data scientists by comparing the detected groups of data scientists' workplaces concerning technostress creators, technostress-related strains, and job performance. Due to our results, we were able to prove that different types of data scientists workplaces are related to different levels and, further, compositions of technostress and related outcomes.

Simultaneously, these detected workplace profiles for data scientists based on several relevant job- and company-related characteristics represent a novelty to the academic discussion regarding the occupational group of data scientists. Thus, the understanding of the data scientist occupation as a heterogeneous group of highly digitalized employees subjected to varying workplace environments is advanced. These four profiles enable a differentiated and systematic examination regarding data scientists' very diverse workplaces and fields of activities. Our findings may facilitate future researchers to conduct more detailed studies of several (and new within today's modern workplace environments, respectively) based on the different profiles of a data scientist. For example, it enables a more differentiated investigation of how the advancement of robotic process automation (e.g., comparing rather interactive profiles like CIL-LE with back office activities of BOE-LE) or the shift towards increasingly agile corporate cultures (e.g., comparing a rather cultural low-level-setting of an CIL-noISB data scientist with the workplace of highly innovative culture of a CIL-LE employee) affect the different data scientist profiles and ultimately reduces or increases their overall job performance.

Comparing our results with prior findings regarding the relationships between workplace attributes and general stress at work, we found both equivalent and contradicting results: while technostress goes along with workplaces exhibiting a leadership function and higher level of bureaucracy which is in line with findings regarding overall work stress (Chan et al., 2000; Ganster, 2005; Hambrick et al., 2005), a higher level of education surprisingly appears to be associated with technostress as well, disagreeing

with the relationship of work stress and education (Golubic et al., 2009). Moreover, technostress is associated with the use of many ICT at work independent of a rare usage while the frequent use of less technologies does not go along with higher technostress. The results further suggest that customer contact is also related to technostress perception which is in line with the relationship of customer contact and overall stress at work (Hartline & Ferrell, 1996). In contrast, there are no clear impacts regarding the presence of large companies as well as high levels of both innovative and supportive culture since these attributes go along with both minor and major technostress issues.

## 5.2 Practical implications

Our study provides several practical aspects for employers who aim to protect their employees effectively from technostress. It is noteworthy that even employees with highly digitalized workplaces like data scientists perceive technostress to a challenging level, varying its composition related to workplace characteristics. Managers are therefore recommended to be aware of the important topic of stress due to ICT usage not only for employees with less technological skills but also for occupational groups which occur a large degree of digitalization, making sure that these employees holding a crucial role for the enterprise's competitive advantages are able to enhance job performance. For providing associated active and successful prevention measures, the variability of perceived technostress between the four types of data scientist workplaces suggests implementing different strategies for dealing with technostress within each group.

Overall, CIL-LE workplaces are associated with the highest level of both technostress creators and strains due to ICT use, so this class requires the highest support in overcoming technostress. As part of support, employers are recommended to explain both the launch process and the requirements of new ICT developments timely and in more detail for countering techno-uncertainty as well as to establish a single point of contact for employees where they may provide feedback whether a technology use is efficient for monitoring techno-overload. Furthermore, managers are suggested to protect the blurring boundaries between work and leisure by limiting employees' availability to their work time for tackling techno-invasion as well as to periodically communicate with their data scientists, underlining that they are important for the company in order to overcome techno-insecurity.

Regarding CIL-noISB incumbents, employers should concentrate on providing support regarding the use of the numerous ICT which have to be handled at these workplaces. By replacing redundant technologies and providing further tutorials for the remaining ones as well as explaining recent developments regarding the ICT used with-

in the company, data scientists will be able to gain more profound and required know-how and the perceived strains due to techno-uncertainty and techno-complexity may be significantly reduced. Moreover, CIL-noISB incumbents should also be supported in protecting blurred boundaries, e.g., by defining clear rules regarding home office or the private use of ICT provided by the company such as mobile phones and laptops. Finally, since these workplaces are associated with significantly lower job performance than all other classes, appreciating achieved productivity is highly recommended.

Since CSM-SME and BOE-LE incumbents generally report relatively low values in technostress and, at the same time, good performance, we suggest focusing on appreciating these groups of data scientists. Further, general support regarding technostress by providing knowledge about the topic and strategies to overcome technostress is recommended.

Generally, the appreciation for the existence of technostress among highly digitalized workplaces will contribute to improved working conditions among data scientists. Increasing awareness and sensitizing for the negative aspects of digitalization among data scientists will positively attribute to work satisfaction and performance. Due to the central contribution of data scientists to the data-driven decision-making within firms, they dispose of critical impact on the overall company performance and subsequently demand special attention.

### 5.3 Limitations and future research

Even though this paper is able to offer a deeper understanding of the heterogeneous and highly relevant job class of data scientists and, further, the level of technostress within these jobs, our investigations have several limitations that have to be taken into account. First, a self-reporting survey in the context of technostress is generally in danger of social desirability bias. Second, we used eight important workplace attributes for detecting classes of data scientist workplaces, but, at the same time, more indicators could help differentiate workplaces, for example, the possibility of using home office or flex time, which was not part of our study. Third, since we aimed to measure the overall level of strains in the context of technostress creators, we could not provide evidence regarding more fine-grained distinctions of strain, e.g., the various facets of burnout or different health issues. Lastly, we asked participants for their overall job performance which does not exhibit a certain causality to the technostress level.

Nevertheless, we were able to provide a deeper understanding of data scientists' workplaces as a job class which has reached particular importance due to the rapid evolution of digitalization at work. Moreover, we proved that technostress should also

be considered in the context of individual job classes in order to effectively deal with it. Therefore, our investigations may be seen as a first step for future examinations of technostress within specific job classes and, further, with respect to other workplace as well as personal attributes to distinguish the necessary internal and external resources to effectively deal with technostress. In this context, future studies regarding how employees' personal characteristics, education, and further personal and workplace factors affect perceived technostress could provide valuable knowledge within the highly relevant interdisciplinary field between psychology and information systems research. Additionally, we recommend to particularly focus on other high-digitalized jobs like, e.g., IT specialists or online marketing experts.

## Acknowledgment

The authors acknowledge the financial support and funding by the German Federal Ministry of Education and Research—BMBF (funding agreement number: 02L16D035 and 02L16D030) for the project PräDiTec—Prävention für gesundes und sicheres Arbeiten mit digitalen Technologien. Further, we would like to thank our student assistant Ivan Kharitonov as well as our former colleague Julia Becker for the support during the preparation of this manuscript.

## References

- Akaike, H., (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6), 716–723.
- Apt, W., Bovenschulte, M., Hartmann, E. A., and Wischmann, S., (2016). *Foresight-Studie „Digitale Arbeitswelt“*. Forschungsbericht, Berlin (accessible from <https://nbn-resolving.org/urn:nbn:de:0168-ssoar-47039-5>).
- Atanasoff, L., and Venable, M. A., (2017). Technostress: Implications for adults in the workforce. *The Career Development Quarterly*, 65(4), 326–338.
- Ayyagari, R., Grover, V., and Purvis R., (2011). Technostress: Technological antecedents and implications. *Management Information Systems Quarterly*, 35(4), 831–858.

- Bakker, A. B., and Demerouti, E., (2017). Job demands-resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology*, 22(3), 273–285.
- Bakker, A. B., van Emmerik, H., and van Riet, P., (2008). How job demands, resources, and burnout predict objective performance: A constructive replication. *Anxiety, Stress, & Coping*, 21(3), 309–324.
- 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*, 35(3), 350–362.
- Baškarada, S., and Koronios, A., (2017). Unicorn data scientist: the rarest of breeds. *Program*, 51(1), 65–74.
- Becker, J., Berger, M., Gimpel, H., Lanzl, J., and Regal, C., (2020). Considering characteristic profiles of technologies at the digital workplace: The influence on technostress. *Proceedings of the Forty-First International Conference on Information Systems (ICIS)*, 1-17.
- Becker, J., Derra, N. D., Regal, C., and Kühlmann, T. M., (2021). Mitigating the negative consequences of ICT use: The moderating effect of active-functional and dysfunctional coping. *Journal of Decision Systems*, 1-33.
- Benlian, A., (2020). A daily field investigation of technology-driven spillovers from work to home. *Management Information Systems Quarterly*, 44(3), 1259-1300.
- Botta, D., Werlinger, R., Gagné, A., Beznosov, K., Iverson, L. and Fels, S.: Fisher, B., (2007). Towards understanding IT security professionals and their tools. *Proceedings of the 3rd symposium on usable privacy and security (SOUPS)*, 100–111.
- Britto, R., Cruzes, D. S., Smite, D. and Sablis, A., (2018). Onboarding software developers and teams in three globally distributed legacy projects: A multi-case study. *Journal of Software: Evolution and Process*, 30(4), 1-17.
- Brod, C., (1984). *Technostress: The human cost of the computer revolution*, Addison-Wesley, Reading.

- Califf, C. B., Sarker, S., and Sarker, S., (2020). The bright and dark sides of technostress: A mixed-methods study involving healthcare IT. *Management Information Systems Quarterly*, 44(2), 809-856.
- 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), 267–283.
- Chan, K. B., Lai, G., Ko, Y. C., and Boey, K. W., (2000). Work stress among six professional groups: the Singapore experience. *Social Science & Medicine*, 50(10), 1415–1432.
- Chang, S. J., van Witteloostuijn, A., and Eden, L., (2010). From the editors: Common-method variance in international business research. *Journal of International Business Studies*, 41(2), 178–184.
- 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), 16–36.
- Cijan, A., Jenič, L., Lamovšek, A., & Stemberger, L., (2019). How digitalization changes the workplace. *Dynamic Relationships Management Journal*, 8(1), 3–12.
- Cooper, C. L., Dewe, P. J., and O'Driscoll, M. P., (2001). *Organizational stress: A review and critique of theory, research, and applications*, Sage Publications, Thousand Oaks.
- Costa, C., and Santos, M. Y., (2017). The data scientist profile and its representativeness in the European e-Competence framework and the skills framework for the information age. *International Journal of Information Management*, 37(6), 726–734.
- Costello, A. B., and Osborne, J., (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research, and Evaluation*, 10(1), 7.

- Coldwell, A. L. D., (2019). Negative influences of the fourth industrial revolution on the workplace, towards a theoretical model of entropic citizen behavior in toxic organizations. *International Journal of Environmental Research and Public Health*, 16(15), 26–70.
- 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, 378-388.
- Davenport, T., (2020). Beyond unicorns: Educating, classifying, and certifying business data scientists. *Harvard Data Science Review*, 2(2).
- Davenport, T. H., and Patil, D. J., (2012). Data scientist. *Harvard Business Review*, 90(5), 70–76.
- Dekker, I., and Barling, J., (1995). Workforce size and work-related role stress. *Work & Stress*, 9(1), 45–54.
- Derks, D., Brummelhuus, L., Zecic, A., and Bakker, A., (2014). Switching on and off: Does smartphone use obstruct the possibility to engage in recovery activities?. *European Journal of Work and Organizational Psychology*, 23(1), 80-90.
- Dima, G., Meseşan Schmitz, L., and Şimon, M.-C., (2021). Job stress and burnout among social workers in the VUCA world of COVID-19 pandemic. *Sustainability*, 13(13), 7109.
- Doyle, A., (2019). *Important job skills for data scientists*. <https://www.thebalancecareers.com/list-of-data-scientist-skills-2062381>, Accessed October 7, 2020.
- Federal Statistical Office of Germany, (2018a). Erwerbstätige und Arbeitnehmer nach Wirtschaftsbereichen je 1.000 Personen [Employees by economic sector by unit of 1,000 persons]. <https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Erwerbstaetigkeit/Tabellen/arbeit>, Accessed October 12, 2020.
- Federal Statistical Office of Germany, (2018b). Erwerbstätige und Erwerbstätigenquote nach Geschlecht und Alter 2008 und 2018: Ergebnis des Mikrozensus [Employment and employment rate by gender and age in 2008 and 2018: Results



of the microzensus]. <https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Erwerbstaetigkeit/Tabellen/erwerbstaetige-erwerbstaetigenquote.html>, Accessed October 12, 2020.

Feir-Walsh, B. J., and Toothaker, L. E., (1974). An empirical comparison of the anova f-test, normal scores test and kruskal-wallis test under violation of assumptions. *Educational and Psychological Measurement*, 34(4), 789–799.

Ferraris, A., Mazzoleni, A., Devalle, A., and Couturier, J., (2019). Big data analytics capabilities and knowledge management: impact on firm performance. *Management Decision*, 57(8), 1923–1936.

Fischer, T., and Riedl, R., (2017). Technostress research: A nurturing ground for measurement pluralism?. *Communications of the Association for Information Systems*, 40(1), 375-401.

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), 1–22.

Fitzgerald, M., Kruschwitz, N., Bonnet, D., and Welch, M., (2013). Embracing digital technology. A new strategic imperative. *MIT Sloan Management Review*, 55(2), 1-16.

Ganster, D. C., (2005). Response: Executive job demands: Suggestions from a stress and decision-making perspective. *Academy of Management Review*, 30(3), 492–502.

Galluch, P. S., Grover, V., and Thatcher, J. B., (2015). Interrupting the workplace: Examining stressors in an information technology context. *Journal of the Association for Information Systems*, 16(1), 1-47.

German Federal Employment Agency, (2020). *Berufenet. Berufsinformationen einfach finden*. <https://berufenet.arbeitsagentur.de/berufenet/faces/index?path=null/suchergebnisse/kurzbeschreibung&dkz=129987&such=data+scientist>, Accessed October 6, 2020.

- Gimpel, H., Lanzl, J., Manner-Romberg, T., and Nüsken, N., (2018). Digitaler Stress in Deutschland. Eine Befragung von Erwerbstätigen zu Belastung und Beanspruchung durch Arbeit mit digitalen Technologien, Hans-Böckler-Stiftung, Düsseldorf.
- Gimpel, H., Lanzl, J., Regal, C., Urbach, N., Wischniewski, S., Tegtmeier, P., Kreilos, M., Kühlmann, T. M., Becker, J., Eimecke, J., and Derra, N. D., (2019). *Gesund digital arbeiten!?: Eine Studie zu digitalem Stress in Deutschland*, Projektgruppe Wirtschaftsinformatik des Fraunhofer FIT, Augsburg.
- Golubic, R., Milosevic, M., Knezevic, B., and Mustajbegovic, J., (2009). Work-related stress, education and work ability among hospital nurses. *Journal of Advanced Nursing*, 65(10), 2056–2066.
- Grace, M. K., and van Heuvelen, J. S., (2019). Occupational variation in burnout among medical staff: evidence for the stress of higher status. *Social Science & Medicine*, 232, 199–208.
- Hackman, J., and Oldham, G. R., (1976). Motivation through the design of work: test of a theory. *Organizational Behavior and Human Performance*, 16(2), 250–279.
- Hageman, S. J., (1992). Alternative methods for dealing with nonnormality and heteroscedasticity in paleontological data. *Journal of Paleontology*, 857–867.
- Hambrick, D. C., Finkelstein, S., and Mooney, A. C., (2005). Executive job demands: New insights for explaining strategic decisions and leader behaviors. *Academy of Management Review*, 30(3), 472–491.
- Harman, H. H., (1967). *Modern factor analysis*, University of Chicago, Chicago
- Hartl, E., (2019). A characterization of culture change in the context of digital transformation. In: G. Rodríguez-Abitia and C. Ferran (Eds.), *25th Americas Conference on Information Systems (AMCIS)*, Cancún, Mexico, pp. 1-10.
- Hartline, M. D., and Ferrell, O. C., (1996). The management of customer-contact service employees: An empirical investigation. *Journal of Marketing*, 60(4), 52–70.

- 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), 115-135.
- Ho, A., Nguyen, A., Pafford, J. L., and Slater, R., (2019). A data science approach to defining a data scientist. *SMU Data Science Review*, 2(3), 1-21.
- Holm, S., (1979). A simple sequentially rejective multiple test procedure. *Scandinavian journal of statistics*, 6(2), 65–70.
- Houtman, I., (2005). *Work-related stress*. European Foundation for the Improvement of Living and Working Conditions. <https://www.eurofound.europa.eu/publications/article/2005/work-related-stress>
- Howard, M. C., (2016). A review of exploratory factor analysis decisions and overview of current practices: What we are doing and how can we improve?. *International Journal of Human-Computer Interaction*, 32(1), 51-62.
- Ismail, N. A., and Abidin, A. Z., (2016). Data scientist skills. *Journal of Mobile Computing & Application*, 3(4), 52–61.
- Janssen, M., van der Voort, H., and Wahyudi, A., (2017). Factors influencing big data decision-making quality. *Journal of Business Research*, 70(1), 338–345.
- Jääskeläinen, A., (2015). *Digitalization and work life: How new technologies are changing task content and skill demand for five selected occupations*. [Master's Thesis, Department of Economics, Aalto University]. <https://aaltodoc.aalto.fi:443/handle/123456789/19321>, Accessed October 10, 2021.
- Lansisalmi, H., Peiro, J. M., and Kivimaki, M., (2000). Collective stress and coping in the context of organizational culture. *European Journal of Work and Organizational Psychology*, 9(4), 527–559.
- Lazarus, R. S., and Folkman, S., (1984). *Stress, appraisal, and coping*, Springer publishing company, New York.

- Linzer, D. A., and Lewis, J. B., (2011). poLCA: An R package for polytomous variable latent class analysis. *Journal of Statistical Software*, 42(10), 1–29.
- Lycett, M., (2013). ‘Datafication’: Making sense of (big) data in a complex world. *European Journal of Information Systems*, 22(4), 381–386.
- Manieri, A., Brewer, S., Riestra, R., Demchenko, Y., Hemmje, M., Wiktorski, T., Ferrari, T., and Frey, J., (2015). *Data science professional uncovered: How the EDISON project will contribute to a widely accepted profile for data scientists*. In: Proceedings of the 7th IEEE International Conference on Cloud Computing Technology and Science (CloudCom’15), Washington DC, United States, pp. 588–593.
- Mauro, A. de, Greco, M., Grimaldi, M., and Ritala, P., (2018). Human resources for big data professions: A systematic classification of job roles and required skill sets. *Information Processing & Management*, 54(5), 807–817.
- Mikalef, P., Giannakos, M. N., Pappas, I. O. and Krogstie, J., (2018). The human side of big data: Understanding the skills of the data scientist in education and industry. In: C.S. González, M. Castro, and M. Llamas (Eds.), *Global Engineering Education Conference (EDUCON)*, Tenerife, Spain, pp. 503–512.
- 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), 525–559.
- Müller, O., Fay, M., and vom Brocke, J., (2018). The effect of big data and analytics on firm performance: An econometric analysis considering industry characteristics. *Journal of Management Information Systems*, 35(2), 488–509.
- Murawski, M., and Bick, M., (2017). Digital competences of the workforce—a research topic? *Business Process Management Journal*, 23(3), 721–734.
- Murgu, C., (2021). “A modern disease of adaptation...”? Technostress and academic librarians working in digital scholarship at ARL institutions. *The Journal of Academic Librarianship*, 47(5), 102400.

- Nylund, K. L., Asparouhov, T., and Muthén, B. O., (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A multidisciplinary Journal*, 14(4), 535–569.
- Okkonen, J., Vuori, V., and Palvalin, M., (2019). Digitalization changing work: Employees' view on the benefits and hindrances. In: Á. Rocha, C. Ferrás, and M. Paredes (Eds.), *Information Technology and Systems. Proceedings of ICITS 2019*, Cham, Switzerland, pp. 165–176
- Osmundsen, K., Iden, J., and Bygstad, B., (2018). *Digital transformation drivers, success factors, and implications*. In: The 12th Mediterranean Conference on Information Systems (MCIS). Corfu, Greece.
- 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. *The Journal of Applied Psychology*, 88(5), 879–903.
- R Development Core Team, (2019). *R: A language and environment for statistical computing*, R Foundation for Statistical Computing, Vienna.
- 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), 417–433.
- Rees, D., and Cooper, C. L., (1992). Occupational stress in health service workers in the UK. *Stress Medicine*, 8(2), 79–90.
- Richards, D., and Marrone, M., (2014). Identifying the education needs of the business analyst: An Australian study. *Australasian Journal of Information Systems*, 18(2).
- RStudio Team, (2019). RStudio: Integrated development environment for R, PCB, Boston.

- Şahin, Y. L., and Çoklar, A. N., (2009). Social networking users' views on technology and the determination of technostress levels. *Procedia—Social and Behavioral Sciences*, 1(1), 1437–1442.
- Salanova, M., Llorens, S., Cifre, E., and Nogareda, C., (2007). El tecnoestrés: Concepto, medida e intervención psicosocial. [Technostress: Concept, measurement and prevention], INSHT, Madrid.
- Salo, M., Pirkkalainen, H., Chua, C. E. H., and Koskelainen, T., (2022). Formation and mitigation of technostress in the personal use of IT. *Management Information Systems Quarterly*, 46.
- 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), 337–363.
- Scaramuzzino, G., and Barfoed, E. M., (2021). Swedish social workers' experiences of technostress. *Nordic Social Work Research*, 1-14.
- Schwarz, G., (1978). Estimating the dimension of a model. *The Annals of Statistics*, 6(2), 461–464.
- Schwemmler, M., and Wedde, P. (Eds.), (2012). *Digitale Arbeit in Deutschland. Potenziale und Problemlagen*, Friedrich-Ebert-Stiftung, Medienpolitik, Bonn.
- 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), 355–401.
- Stadin, M., Nordin, M., Broström, A., Hanson, L. L. M., Westerlund, H., and Fransson, E. I., (2021). Technostress operationalised as information and communication technology (ICT) demands among managers and other occupational groups—results from the Swedish longitudinal occupational survey of health (SLOSH). *Computers in Human Behavior*, 114, 1–9.

- Stanton, A. D., and Stanton, W. W., (2016). The relationship between big data, data science, digital analytics and the skills and abilities needed to optimise marketing decisions. *Applied Marketing Analytics*, 2(3), 265–279.
- 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), 6–42.
- 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), 96-124.
- Tarafdar, M., Pullins, E., and Ragu-Nathan, T. S., (2015). Technostress: Negative effect on performance and possible mitigations. *Information Systems Journal*, 25(2), 103–132.
- 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), 301–328.
- 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), 303–334.
- Tarafdar, M., Tu, Q., Ragu-Nathan, T. S., and 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.
- Taris, T. W., (2006). Is there a relationship between burnout and objective performance? A critical review of 16 studies. *Work & Stress*, 20(4), 316–334.
- Tehseen, S., Ramayah, T. and Sajilan, S., (2017). Testing and controlling for common method variance: A review of available methods. *Journal of Management Sciences*, 4(2), 142–168.

- Thompson, N., Stradling, S., Murphy, M., and O’neill, P., (1996). Stress and organizational culture. *The British Journal of Social Work*, 26(5), 647–665.
- Timonen, H. and Vuori, J., (2018). *Visibility of work: How digitalization changes the workplace*. In: Proceedings of the 51st Hawaii International Conference on System Sciences. Waikoloa Village, HI, USA.
- 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*, 21(1), 19–25.
- Travers, C. J., and Cooper, C. L., (1993). Mental health, job satisfaction and occupational stress among UK teachers. *Work & Stress*, 7(3), 203–219.
- Tucker, J. W., (1994). Generalized van der Waerden identities. *Journal of Physics A: Mathematical and General*, 27(3): 659–662.
- U. S. Bureau of Labour Statistics (2021). *Fastest growing occupations, 2020 and projected 2030, excluding occupations with above average cyclical recovery*. <https://www.bls.gov/emp/tables/fastest-growing-occupations-alt.htm>. Accessed October 12, 2021.
- Vaast, E., and Pinsonneault, A., (2021). When digital technologies enable and threaten occupational identity: The delicate balancing act of data scientists. *Management Information Systems Quarterly*, 45(3), 1087-1112.
- van der Waerden, B. L., (1952). Order tests for the two-sample problem and their power. *Indagationes Mathematicae*, 14(1), 453–458.
- van Dijkhuizen, N., and Reiche, H. M., (1980). Psychosocial stress in industry: A heartache for middle management? *Psychotherapy and Psychosomatics*, 34(2-3), 124–134.
- Vargha, A., and Delaney, H. D., (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), 101–132.



- Wallach, E. J., (1983). Individuals and organizations: The cultural match. *Training and Development Journal*, 37(2), 29–36.
- Waller, M. A., and Fawcett, S. E., (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics*, 34(2), 77–84.
- Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., and Childe, S. J., (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70(1), 356–365.

## Appendix 1

<i>CIL-noISB</i>		<i>CIL-LE</i>		<i>BOE-LE</i>	
<i>Creator</i>	<i>Strain</i>	<i>Creator</i>	<i>Strain</i>	<i>Creator</i>	<i>Strain</i>

<i>Techno-Uncertainty</i>						
<i>CSM-SME</i>	1.000	0.180	< <b>0.001</b>	0.100	1.000	1.000
<i>CIL-noISB</i>	-	-	< <b>0.001</b>	1.000	1.000	0.350
<i>CIL-LE</i>	-	-	-	-	< <b>0.001</b>	0.300
<i>BOE-LE</i>	-	-	-	-	-	-
<i>Techno-Insecurity</i>						
<i>CSM-SME</i>	0.481	0.072	<b>0.001</b>	<b>0.006</b>	> 0.5	1.000
<i>CIL-noISB</i>	-	-	0.147	1.000	> 0.5	<b>0.025</b>
<i>CIL-LE</i>	-	-	-	-	0.067	< <b>0.001</b>
<i>BOE-LE</i>	-	-	-	-	-	-

<i>Techno-Overload</i>						
<i>CSM-SME</i>	1.000	0.080	0.350	<b>0.037</b>	1.000	> 0.5
<i>CIL-noISB</i>	-	-	0.390	> 0.5	1.000	0.443
<i>CIL-LE</i>	-	-	-	-	1.000	0.434
<i>BOE-LE</i>	-	-	-	-	-	-
<i>Techno-Invasion</i>						
<i>CSM-SME</i>	> 0.5	0.277	0.134	<b>0.007</b>	0.134	0.418
<i>CIL-noISB</i>	-	-	0.066	0.418	0.134	<b>0.017</b>
<i>CIL-LE</i>	-	-	-	-	<b>&lt; 0.001</b>	<b>&lt; 0.001</b>
<i>BOE-LE</i>	-	-	-	-	-	-
<i>Techno-Complexity</i>						
<i>CSM-SME</i>	0.319	> 0.5	0.261	> 0.5	1.000	> 0.5
<i>CIL-noISB</i>	-	-	1.000	> 0.5	0.155	<b>0.026</b>
<i>CIL-LE</i>	-	-	-	-	0.075	<b>0.015</b>
<i>BOE-LE</i>	-	-	-	-	-	-

Table 6. p-values for the pairwise van der Waerden tests comparing the types of workplaces regarding technostress creators; bold values indicate significant results with  $\alpha = 5\%$  with Holm–Bonferroni correction (Holm, 1979)

	<i>CIL-noISB</i>	<i>CIL-LE</i>	<i>BOE-LE</i>
<i>CSM-SME</i>	<b>&lt; 0.001</b>	0.079	0.079
<i>CIL-noISB</i>	-	<b>&lt; 0.001</b>	<b>&lt; 0.001</b>
<i>CIL-LE</i>	-	-	<b>&lt; 0.001</b>
<i>BOE-LE</i>	-	-	-

Table 7. p-values for the pairwise van der Waerden tests comparing the types of workplaces regarding job performance; bold values indicate significant results with  $\alpha = 5\%$  with Holm–Bonferroni correction (Holm, 1979)

## Appendix 2

<i>CIL-noISB</i>		<i>CIL-LE</i>		<i>BOE-LE</i>	
<i>Creator</i>	<i>Strain</i>	<i>Creator</i>	<i>Strain</i>	<i>Creator</i>	<i>Strain</i>

<i>Techno-Uncertainty</i>						
<i>CSM-SME</i>	0.498	0.397	<b>0.337</b>	0.405	0.467	0.474
<i>CIL-noISB</i>	-	-	<b>0.329</b>	0.504	0.472	0.578
<i>CIL-LE</i>	-	-	-	-	<b>0.668</b>	0.572
<i>BOE-LE</i>	-	-	-	-	-	-
<i>Techno-Insecurity</i>						
<i>CSM-SME</i>	0.421	0.388	0.364	0.382	0.452	0.525
<i>CIL-noISB</i>	-	-	0.423	0.489	0.546	0.630
<i>CIL-LE</i>	-	-	-	-	0.613	<b>0.640</b>
<i>BOE-LE</i>	-	-	-	-	-	-

<i>Techno-Overload</i>						
<i>CSM-SME</i>	0.479	0.385	0.423	0.392	0.461	0.459
<i>CIL-noISB</i>	-	-	0.429	0.504	0.481	0.570
<i>CIL-LE</i>	-	-	-	-	0.539	0.564
<i>BOE-LE</i>	-	-	-	-	-	-
<i>Techno-Invasion</i>						
<i>CSM-SME</i>	0.490	0.406	0.416	0.384	0.572	0.552
<i>CIL-noISB</i>	-	-	0.409	0.466	0.600	<b>0.650</b>
<i>CIL-LE</i>	-	-	-	-	<b>0.672</b>	<b>0.666</b>
<i>BOE-LE</i>	-	-	-	-	-	-
<i>Techno-Complexity</i>						
<i>CSM-SME</i>	0.406	0.417	0.435	0.446	0.518	0.552
<i>CIL-noISB</i>	-	-	0.509	0.516	0.624	0.637
<i>CIL-LE</i>	-	-	-	-	0.589	0.603
<i>BOE-LE</i>	-	-	-	-	-	-

Table 8. Vargha and Delaney's A for for the pairwise comparisons of the types of workplaces regarding technostress creators; bold values indicate moderate or strong effects (Tomczak & Tomczak 2014); grey values are not significant

## Derra et al.: Examining Technostress at Different Types of Data Scientists' Workplaces

	<i>CIL-noISB</i>	<i>CIL-LE</i>	<i>BOE-LE</i>
<i>CSM-SME</i>	<b>0.737</b>	0.433	0.588
<i>CIL-noISB</i>	-	<b>0.211</b>	<b>0.343</b>
<i>CIL-LE</i>	-	-	<b>0.646</b>
<i>BOE-LE</i>	-	-	-

Table 9. Vargha's and Delayne's A for the pairwise comparison of the types of workplaces regarding job performance; bold values indicate moderate and strong effects (Tomczak & Tomczak 2014); grey values are not significant

## Appendix 3

<i>Aspect</i>	<i>Indicators</i>	<i>Characteristic</i>	<i>Latent Class</i>				
			<i>CSO-SME (83)</i>	<i>CIL-noISB (91)</i>	<i>CIL-LE (225)</i>	<i>BOE-LE (87)</i>	<i>All</i>
<i>Job</i>	<i>Customer Contact</i>	<i>Yes</i>	74	79	190	42	385
		<i>No</i>	9	12	35	45	101
	<i>Leadership Function</i>	<i>Yes</i>	49	62	208	12	331
		<i>No</i>	34	29	17	75	155
	<i>Requirement Level</i>	<i>Non-academic</i>	71	35	67	43	216
		<i>Academic</i>	12	65	158	44	270
	<i>Degree of Digitalization</i>	<i>Few, Rarely</i>	10	18	14	14	56
		<i>Few, Often</i>	57	25	37	61	180
		<i>Many, Rarely</i>	9	32	96	4	141
		<i>Many, Often</i>	7	16	78	8	109
<i>Company</i>	<i>Company Size</i>	<i>less than 250</i>	83	56	74	2	215
		<i>250 or more</i>	0	35	151	85	271
	<i>Innovativeness</i>	<i>low</i>	18	84	11	31	144
		<i>high</i>	65	7	214	56	342
	<i>Support</i>	<i>low</i>	15	71	19	46	151
		<i>high</i>	68	20	206	41	335
	<i>Bureaucracy</i>	<i>low</i>	18	91	12	21	142
		<i>high</i>	65	0	213	66	344

Table 10. Number of data scientists exhibiting a certain characteristic within a type of workplace



## Appendix 4

<i>Construct</i>	<i>Items</i>	<i>M</i>	<i>SD</i>	<i>Loadings</i>	<i>Cronbach's α</i>	<i>AVE</i>
<i>Invasion</i>	3	1.65	1.17	0.48-0.91	0.83	0.64
<i>Overload</i>	4	1.97	1.09	0.43-0.70	0.88	0.65
<i>Complexity</i>	5	1.40	1.22	0.76-0.91	0.93	0.72
<i>Insecurity</i>	4	1.59	1.06	0.44-0.79	0.81	0.53
<i>Uncertainty</i>	4	2.24	1.00	0.66-0.85	0.86	0.61
<i>Job Performance</i>	4	2.76	0.81	0.76-0.81	0.87	0.62

Table 11. Descriptive Statistics, Internal Consistency, AVE, and Factor Loadings

<i>Construct</i>	<i>INV</i>	<i>OVE</i>	<i>COM</i>	<i>INS</i>	<i>UNC</i>	<i>JOB</i>
<i>Invasion</i>	<b>0.80</b>					
<i>Overload</i>	0.68	<b>0.81</b>				
<i>Complexity</i>	0.64	0.63	<b>0.85</b>			
<i>Insecurity</i>	0.72	0.72	0.70	<b>0.73</b>		
<i>Uncertainty</i>	0.42	0.50	0.36	0.60	<b>0.78</b>	
<i>Job Performance</i>	-0.03	-0.06	-0.24	-0.06	0.11	<b>0.79</b>

Table 12. Diagonal elements are square root AVE; off-diagonal elements are correlations; INV = Invasion, OVE = Overload, COM = Complexity, INS = Insecurity, UNC = Uncertainty, JOB = Job Performance

## Appendix 5

Table 13. 25%-Quantile, 50%-Quantile, 75%-Quantile, mean (M), and standard deviation (SD) of both technostress creators and related strain, for four classes of data scientists' workplaces; bold values indicate the highest value for a technostress creators/job performance

Type	Construct	Technostress Creator					Strain due to ICT use				
		25% Quantile	50% Quantile	75% Quantile	M	SD	25% Quantile	50% Quantile	75% Quantile	M	SD
CSM-SME (n = 83)	Uncertainty	1.125	2.000	2.875	1.925	1.112	0.000	0.750	2.000	1.051	1.080
	Insecurity	0.400	1.200	1.900	1.282	1.082	0.000	0.600	1.600	0.872	0.992
	Overload	1.000	2.000	2.750	1.795	1.185	0.000	1.000	2.000	1.211	1.119
	Invasion	0.333	1.667	2.500	1.546	1.288	0.000	0.667	2.000	1.108	1.165
CIL-no/LSB (n = 91)	Complexity	0.200	1.000	2.100	1.241	1.127	0.000	0.800	2.000	1.063	1.080
	Job Performance	-	-	-	-	-	2.500	3.000	3.250	2.825	0.775
	Uncertainty	1.125	2.000	2.750	1.926	1.059	0.500	1.500	2.000	<b>1.412</b>	1.031
	Insecurity	0.600	1.800	2.200	1.523	0.968	0.000	1.400	2.000	1.266	1.029
CIL-LE (n = 225)	Overload	1.125	2.000	2.500	1.852	1.005	0.625	2.000	2.500	<b>1.646</b>	1.108
	Invasion	0.500	1.667	2.333	1.557	1.077	0.500	1.667	2.000	1.451	1.004
	Complexity	0.700	1.800	2.200	<b>1.527</b>	0.964	0.200	1.600	2.000	<b>1.336</b>	1.043
	Job Performance	-	-	-	-	-	1.750	2.000	2.750	2.159	0.824
BOE-LE (n = 87)	Uncertainty	2.000	2.750	3.000	<b>2.546</b>	0.885	0.500	1.500	2.000	1.392	1.053
	Insecurity	1.000	2.000	2.400	<b>1.800</b>	1.066	0.200	1.200	2.000	<b>1.308</b>	1.101
	Overload	1.500	2.250	2.750	<b>2.080</b>	1.049	0.500	1.750	2.500	1.623	1.126
	Invasion	1.000	2.000	2.667	<b>1.887</b>	1.146	0.333	1.667	2.333	<b>1.596</b>	1.189
BOE-LE (n = 87)	Complexity	0.400	1.400	2.400	1.514	1.197	0.000	1.000	2.200	1.284	1.155
	Job Performance	-	-	-	-	-	2.500	3.000	3.500	<b>3.027</b>	0.693
	Uncertainty	1.625	2.000	2.500	2.060	0.879	0.000	1.000	2.000	1.129	1.076
	Insecurity	0.600	1.200	2.000	1.411	1.028	0.000	0.200	1.400	0.795	0.992
BOE-LE (n = 87)	Overload	1.250	2.000	2.875	1.948	1.186	0.125	1.250	2.250	1.385	1.169
	Invasion	0.000	1.333	2.000	1.215	1.081	0.000	0.333	1.667	0.935	1.126
	Complexity	0.200	1.000	1.900	1.136	1.025	0.000	0.600	1.600	0.887	0.990
	Job Performance	-	-	-	-	-	2.000	2.500	3.000	2.641	0.771