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RESEARCH NOTE

DECONSTRUCTING TECHNOSTRESS: A CONFIGURATIONAL APPROACH TO EXPLAINING JOB BURNOUT AND JOB PERFORMANCE[1]

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Understanding how technostressors lead to technostrain, such as high job burnout or low job performance, has become a core question in information systems (IS) research and practice. To unpack this relationship, we build on general systems theory to argue that the next step for technostress research is to go beyond examining the independent influences of technostressors and discuss how their interdependencies lead to technostrain. To illustrate our argument empirically, we use fuzzy-set qualitative comparative analysis (fsQCA) and identify four configurations of high- and low-intensity technostressors that lead to high job burnout and one that leads to low job performance. We show that three types of interdependencies among technostressors, i.e., complementarity, contingency, and substitution, form configurations that lead to technostrain. Within these configurations, high-intensity technostressors can mutually enhance their effects and low-intensity technostressors can buffer the impact of other high-intensity technostressors on technostrain. The results help to explain why organizational interventions that address independent technostressors may fail if they do not account for the interdependencies among technostressors. Our work provides evidence of the need to further develop theories that explain how and why interdependencies among technostressors lead to technostrain.

Keywords: Technostress, general systems theory, interdependencies, configurations, qualitative comparative analysis (QCA), two-step QCA, two-wave study, job burnout, job performance

[1] Chee-Wee Tan was the accepting senior editor for this paper. John D'Arcy served as the associate editor.

Introduction

Technostress refers to stress derived from the use of information systems (IS) (Ragu-Nathan et al., 2008). It is pervasive in modern work life and leads to severe consequences for employees and organizations alike (Stich et al., 2019; Tarafdar et al., 2015). *Technostressors* can lead to severe consequences in the form of *technostrain*, e.g., low job performance or high job burnout (Srivastava et al., 2015; Tarafdar et al., 2015).

Substantial effort has been invested into understanding the causes (i.e., technostressors) and consequences (i.e., technostrain) of technostress (Ayyagari et al., 2011; Califf et al., 2020). Research has identified multiple technostressors and commonly discusses five of them, including techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty (Ragu-Nathan et al., 2008). Most often, the relationship between technostressors and technostrain has been empirically modeled as either independent or additive. For example, the more an employee is overwhelmed by technology-enabled interruptions (techno-overload) (independent approach) or the more an employee perceives the conglomerate of the five commonly discussed technostressors (aggregate approach), the more technostrain an employee experiences (Galluch et al., 2015; Maier et al., 2019).

Recent indications from investigations of private/leisure IS use suggest that technostressors *combine* to create technostrain (Salo et al., 2019)—for example, techno-overload and techno-invasion combining to create technostrain. However, the intricate interdependencies among the effects of technostressors that lead to (or, in some combinations, even potentially inhibit) technostrain, such as high job burnout or low job performance, have been left unexamined. We thus build upon general systems theory (GST) (Bertalanffy, 1975; Chatterjee et al., 2021) to argue that the *interdependencies* among the effects of technostressors lead to technostrain. For example, being overwhelmed by frequent electronic messages (high-intensity techno-overload) could lead to more job burnout when there is also intrusiveness into time away from work (high-intensity techno-invasion). Interdependencies imply that the high or low intensity of a technostressor makes the effect of another technostressor on technostrain more (or less) powerful. For example, when electronic messages are easy to process (low-intensity techno-complexity), a user may feel less job burnout from high-intensity techno-overload or techno-invasion.

To explore the interdependencies among technostressors, we follow a configurational approach to investigate how configurations, i.e., combinations of well-established technostressors, can lead to technostrain. The configurational approach (Mattke et al., 2022; Mithas et al., 2022) allows us to unveil the complexity of interdependencies among conditions, such as technostressors, that lead to an outcome such as technostrain. We begin with a concise summary of technostress research in the work context. Then, we theorize how three possible interdependencies, i.e., contingency, complementarity, and substitution lead to technostrain. Next, we elaborate on our logic for taking a configurational approach to studying the interdependencies among the effects of technostressors. With our configurational approach, we reveal important and empirically prevalent configurations of technostressors that suggest that additional non-naive relationships between the effects of technostressors create realistic outcomes. We use fuzzy set qualitative comparative analysis (fsQCA) to analyze data gathered from 166 full-time employee participants and demonstrate that configurations that include complementarity, contingency, and/or substitution effects lead to technostrain in the form of high job burnout and low job performance. We conclude with five propositions for future work and discuss our findings.

Theoretical Background

Technostress, Technostressors, Technostrain

Technostress describes a process that begins with an IS stimulus that is appraised by the user as threatening (i.e., a technostressor) and results in adverse consequences (i.e., technostrain) (Ayyagari et al., 2011; Nastjuk et al., 2023). IS research often focuses on five work-relevant technostressors (Ragu-Nathan et al., 2008): techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty (Table 1).

Technostressors have been linked to psychological, behavioral, and physiological technostrain—e.g., psychological technostrain in the form of exhaustion (Chen & Karahanna, 2018), excessive mental workload (Tams et al., 2018), and job burnout (Maier et al., 2019; Srivastava et al., 2015); behavioral technostrain in the form of low job performance (Tarafdar et al., 2015) and low non-job-related performance (Chen & Karahanna, 2018); and physiological technostrain manifested as the release of stress hormones (Galluch et al., 2015; Riedl et al., 2012) and an increase in physiological arousal (Weinert et al., 2022).

Table 1. Work Relevant Technostressors (Ragu Nathan et al., 2008)	
Techno-overload	Conditions in which users are confronted with more work or work that has to be completed faster because of IS
Techno-invasion	Conditions in which users feel the need to be reachable and “connected” at all times and where the line between work and personal life becomes blurred because of IS
Techno-complexity	Conditions in which the complexity of an IS leads users to feel that they have inadequate IS skills and must devote time and effort to understanding the different aspects of IS
Techno-insecurity	Conditions in which users fear that their job position may be replaced by an IS or a colleague with better IS skills and they therefore fear losing their job
Techno-uncertainty	Conditions in which users feel uncertain because they face ongoing changes in IS and constantly need to adapt, learn, and educate themselves about new IS

Technostress research sometimes aggregates the first-order work-relevant technostressors into a higher-order aggregate technostressor construct (Ragu-Nathan et al., 2008; Tarafdar et al., 2019) and studies the impact of the aggregate technostressor construct on technostrain (Maier et al., 2019). For instance, studies in this research stream have found that the higher the aggregate technostressor construct, the higher the technostrain in terms of reduced job performance (Ragu-Nathan et al., 2008). These studies have confirmed a relationship between technostressors and technostrain but have left unexamined the interplay among specific technostressors and their intensities on technostrain.

Recent research has taken a more nuanced approach to the aggregate technostressor construct. For example, Maier et al. (2019) found a quadratic effect of technostressors on technostrain, showing that both a high *and* low intensity of the aggregate technostressor construct, i.e., a high and low value of the aggregate technostressor construct can lead to high technostrain manifested as low job performance. This insight is supported by studies of individual technostressors in the context of a specific technology. For example, Stich et al. (2019) found that users may perceive receiving both too much email and too little email as stressful. These findings highlight the importance of accounting for different intensities of technostressors, ranging from high intensity (i.e., having a high value on the technostressor scale) to low intensity (i.e., having a low value on the technostressor scale) for predicting technostrain. Such work reveals that the relationship between technostressors and technostrain is more complex than previously suggested.

Some research that isolates the effects of individual technostressors has suggested that individual technostressors can exert contrasting effects on technostrain. For example, Chandra et al. (2019) found that while high-intensity techno-insecurity reduces employee innovation, high-intensity techno-uncertainty increases it. Moreover, some research examining technostress in nonwork contexts has suggested an interplay among technostressors. Based on interview data, Salo et al. (2019) found that individual technostressors *together* lead to social relation problems among social networking site users. Drawing on these insights from recent technostress research indicating the complexity of the technostressor-technostrain relationship, we offer a more nuanced perspective on the relationships between technostress and technostrain by disentangling complexities that thus far remain unaccounted for in the extant literature.

A Systemic Perspective on Technostressors Leading to Technostrain

General systems theory (Bertalanffy, 1975; Chatterjee et al., 2021) (GST) suggests that complex human responses—e.g., technostrain in our context—result from a *combination of multiple interdependent components*, such as technostressors. GST implies that the interdependent effects of components result in stable combinations of components in a given situation and that different combinations, in turn, shape human responses to that situation. In the broader stress literature, GST helps to explain why interdependencies among the effects of job stressors and job characteristics shape strain. For instance, Karasek’s (1979) seminal work on job stressors found that job stressors only lead to strain when an employee’s level of job control is low, although low job control alone does not lead to strain. He also found that if job stressors accompany high levels of job control, they may lead to positive work outcomes. By studying interdependencies, GST suggests that technostress research can realize a holistic understanding of how the combined effect of technostressors at different intensity levels differs from the effect of the simple sum of individual technostressors.

Theorizing Interdependencies among Technostressors

To theorize potential interdependencies among technostressors that lead to technostrain, we leverage configurational theorizing as a starting point to consider the interdependencies of *complementarity, contingency,* and *substitution* (Furnari et al., 2021). We then theorize the effects of these interdependencies in technostress research, empirically show their relevance, and derive their implications for technostress research. To illustrate these three interdependencies, we introduce a running illustration of Ben, a teleworking employee.

After a year of working at home, Ben is struggling with two technostressors: Ben's colleagues contact him not only by email but also via instant messaging tools and his mobile phone, leading to constant interruptions when he is trying to focus on assigned tasks. Therefore, Ben feels like he cannot really make progress on tasks that require his full attention (high-intensity techno-overload). At the same time, Ben has noticed that an increasing number of tasks he was previously responsible for are now automated and performed by IS. In light of these changes, Ben fears that he will ultimately become obsolete, with his job being replaced by IS (high-intensity techno-insecurity). With his fear of becoming obsolete in the background, the constant interruptions and the feeling that he is not really making progress exhaust him even more, and the feeling that he is not keeping up with his tasks simultaneously exacerbates the pressure he feels due to job insecurity. Thus, high-intensity techno-overload and high-intensity techno-insecurity mutually enhance their effects on technostrain, which we term *complementarity* between technostressors.

Insights into complementarity are relevant for technostress research and practice. Existing research has identified five widely used technostressors as the causes of technostrain (Ragu-Nathan et al., 2008), suggesting that a high intensity of the aggregate of these five technostressors leads to technostrain. However, this approach bears the risk of overdetermination, meaning that more high-intensity technostressors would appear to be necessary than are actually necessary for technostrain to occur. There is thus a need to investigate which high-intensity technostressors in combination with low-intensity technostressors are sufficient to bring about high job burnout or low job performance. Because of the mutual enhancement of the effect of technostressors (complementarity), not all of the other high-intensity technostressors may be necessary; rather, a subset of high-intensity technostressors may be sufficient for creating technostrain.

Ben is not always exhausted by high-intensity techno-overload and high-intensity techno-insecurity; their effect seems to vary according to the intensity of techno-invasion. When Ben can separate his work and personal life (low-intensity techno-invasion), he is less likely to feel exhausted. In contrast, when Ben is frequently contacted after business hours, the line between his work and private life becomes blurred (high-intensity techno-invasion) and exacerbates his feeling of exhaustion. As this example illustrates, technostressors can have different intensities (i.e., low- vs. high-intensity techno-invasion) and their effects on technostrain may be contingent on the level of other technostressors. We term this phenomenon the *contingency* of technostressors. For instance, in this example, high-intensity techno-overload and high-intensity techno-insecurity evoke technostrain only in the presence of another high-intensity technostressor (high-intensity techno-invasion).

Accounting for contingencies among the effects of technostressors may reveal instances where some combinations of high-intensity technostressors along with other low-intensity technostressors can be tolerated and do not lead to technostrain as long as the contingent technostressor itself is of low intensity. Insight into which combinations are tolerable for employees could inform an understanding of situations in which the need for measures against technostress is not indicated, as employees in such situations do not suffer from job burnout or poor performance. By directing attention to combinations and intensity, studying the interdependencies among technostressors can help practitioners understand the circumstances under which technostressor configurations are more (or less) relevant to technostrain.

Returning to Ben, when his home office situation was still new, he found that technology rarely interrupted his personal time (low-intensity techno-invasion). However, Ben gradually found that the tools designed to facilitate working from home, such as video conferencing, were placing greater demands on his time (high-intensity techno-overload). Beyond that, he also found the new software to be disruptive, requiring him to adjust his work practices (high-intensity techno-uncertainty), which drained his energy and led to exhaustion. As seen in this example, the combination of two high-intensity technostressors can offset the effect of a low-intensity technostressor (techno-invasion) so that the configuration still leads to technostrain, despite the presence of a low-intensity technostressor. We term this phenomenon the *substitution* of technostressors. Substitution implies that the high intensities of some technostressors are offsetting the low intensity of another technostressor.

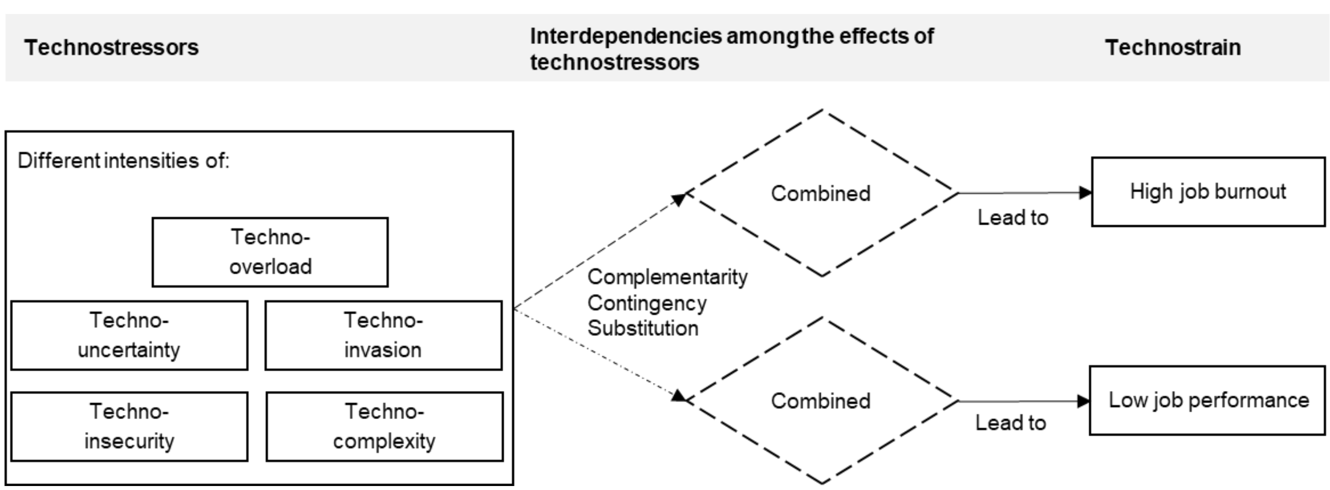
Because of substitution, different configurations of technostressors that may include low-intensity technostressors can lead to high job burnout or low job performance, making a case-based approach relevant to explaining technostrain for different situations and employees. This contrasts with the aggregate approach, which suggests that employees experience technostrain when the aggregate technostressor construct is of high intensity. However, one employee may confront different sets of technostressors—i.e., configurations of technostressors—over the course of their workday. Moreover, one employee may respond to a configuration of technostressors in a different way than another employee. Absent insight into substitution, managers might overlook paths that could cause employee job burnout or low performance due to technostressors.

Our running example illustrates three potential interdependencies and suggests that it is essential to go beyond the aggregate approach to understand technostress.

Accounting for Interdependencies among Technostressors: A Research Approach ■

Our investigation of the interdependencies among technostressors follows a configurational approach (Mithas et al., 2022; Ragin, 2014). We assume that technostressors do not act individually but in concert to lead to technostrain and that they manifest in nontrivial configurations that include complementarity, contingency, and/or substitution effects. Our configurational approach affords opportunities for inductive theorizing, particularly because of the lack of sufficient theory to specify a priori configurations that lead to our outcomes of interest (Park et al., 2020). This is important because while some technostress research has used a configurational approach (Khedhaouria & Cucchi, 2019; Maier et al., 2021; Pflügner et al., 2021), it has not been applied to inductively derive insight into the complex interdependencies among technostressors.

We examine two commonly studied forms of technostrain, namely high job burnout and low job performance, and assume that they stem from different mechanisms (Bakker & Demerouti, 2007). High-intensity technostressors can exhaust employees' resources and deplete energy, eventually resulting in job burnout. However, because of performance protection strategies (Hockey, 1997), this depletion of energy does not necessarily result in low job performance. Further, high-intensity technostressors can deplete motivation, resulting in less work engagement and, eventually, low job performance. Based on these different mechanisms, we assume that high job burnout and low job performance can result from diverging configurations of technostressors. We derive the following nomological net (Figure 1).



Note: Dotted rhombuses and arrows are theoretical considerations inherent in the paper, black rectangles are the constructs assessed in the survey.

Figure 1. Nomological Network

Method

To map interdependencies to configurations, we used fsQCA (Ragin, 2014) and focused on identifying *sufficient configurations*, meaning that when a certain configuration of technostressors exists, users experience technostrain. We followed the common steps suggested in the literature to generate valid and robust results from our fsQCA (Mattke et al., 2022).

Data Collection and Demographics

With top management support, we collected survey data from an international automotive supplier with around 4,000 employees working in multiple locations and annual sales of about 500 million USD. The company contacted the authors because they were experiencing issues with technostress; they provided us with access to 200 randomly selected employees in Germany. These employees were using IS in nearly all of their daily work processes. The IS they used ranged from enterprise and database technologies (e.g., SAP CRM, SAP ECC) to mobile (e.g., smartphone), network (e.g., VPN), and communication (e.g., email, Microsoft Teams) technologies. We gathered data on technostressors and technostrain in two waves in 2018, leaving six weeks between surveys. The first wave of data collection captured data about technostressors and the second captured data about technostrain. 191 employees (95.50%) participated in the first wave, and 166 of those employees (86.91%) participated in the second wave. Table 2 provides demographic information.

Measures, Measurement Model, and Common Method Bias

We used 23 items to measure five technostressors (Ragu-Nathan et al., 2008), nine items to measure job burnout (Srivastava et al., 2015), and six items (Tarafdar et al., 2010) to measure job performance (Appendix A). All items used a 7-point Likert scale ranging from 1 (*strongly disagree*), reflecting the lowest intensity of the item, to 7 (*strongly agree*), reflecting the highest intensity. Our evaluation of item reliability, internal consistency reliability, convergent validity, and discriminant validity showed that the measures are reliable and valid (Liu et al., 2017) and testing suggested that common method bias (CMB) did not impact our results (Appendix B).

Configurational Data Analysis

fsQCA required transforming the Likert-scale values into fuzzy values, which refers to calibration. We modeled each technostressor as a *fuzzy value*, which ranges from 0 to 1 and expresses the degree to which a technostressor is a high-intensity and low-intensity technostressor. For instance, a fuzzy value of 0.66 reflects a rather high-intensity technostressor that also has some qualities of a low-intensity technostressor. We calculated the mean value of all items of the construct in the data set (Liu et al., 2017). Then, we used direct calibration, setting three different anchors of membership for each construct. We set the full membership value at the Likert-scale value of 7; thus, a mean value of 7 transfers to the fuzzy value of 1. The point of maximum ambiguity was set at the Likert-scale value of 4. This means that a mean value of 4 transfers to a fuzzy value of 0.50 and cannot be attributed to either the high-intensity or low-intensity technostressor. The full non-membership value was set to the Likert-scale value of 1, so that a mean value of 1 transfers to a fuzzy value of 0, i.e., the technostressor is clearly a low-intensity technostressor. Based on these three anchors, the direct calibration used a logistic function to fit all Likert-scale values between the three anchors. We performed several sensitivity analyses with other calibration anchors to ensure the robustness of the results and followed the standard protocol for fsQCA (Appendix C). We used the fsQCA software 3.0 and the R QCA software.

Results

The analysis identified four sufficient configurations (C) of technostressors that lead to high job burnout (C1 to C4) and one configuration that leads to low job performance (C5) (Figure 2).

The QCA results were assessed based on two general measures: coverage and consistency (Table 3). Coverage serves an analogous purpose like the coefficient of determination (R^2) (Mithas et al., 2020), whereas consistency serves an analogous purpose like the significance in regression analysis (Greckhamer et al., 2018). Both measures can be calculated on the basis of one specific configuration (second row in Figure 2) or on the overall result (last row in Figure 2).

The equal solution consistencies of 0.88 (Figure 2) for the sufficient configurations for high job burnout and low job performance demonstrate that the configurations of both are equally suited to explaining technostrain. The solution coverage for high job burnout is 0.44, which indicates that the four identified sufficient configurations have adequate explanatory power, analogous to the solution coverage for low job performance of 0.34. The raw coverages for high job burnout and low job performance exceed the value of 0, which indicates that each configuration contributes to the explanation of high job burnout or low job performance (Liu et al., 2017; Schneider & Wagemann, 2012).

Table 2. Demographics of 166 Participants for the Two Wave Study in Percentages	
Age (mean: 34.71; standard deviation: 10.86)	
<31	47.13
31-40	29.32
41-50	12.74
>50	10.81
Gender	
Male	54.49
Female	45.51
Other	0.00

Condition \ Configuration	High job burnout				Low job performance
	C1	C2	C3	C4	C5
Techno-overload	●	●	●	●	●
Techno-invasion	●	●	●	○	●
Techno-complexity	●	●	○	●	●
Techno-insecurity	●	●	●	●	●
Techno-uncertainty	●	○	●	●	●
Raw/unique/solution coverage	0.33	0.18	0.24	0.23	0.34
Consistency/solution consistency	0.91	0.94	0.92	0.94	0.88
Solution coverage (minimized solution)	0.44				0.34
Solution consistency (minimized solution)	0.88				0.88

Notes: ● = high intensity, ○ = low intensity, C = configuration

Figure 2. Configurations Leading to High Job Burnout and Low Job Performance

Table 3. Definitions of QCA Measures (Schneider & Wagemann, 2012)	
Raw coverage	Extent to which configurations leading to the outcome of interest in the data set can be described by the specific sufficient configuration
Consistency	Extent to which the specific configuration is a sufficient configuration for the outcome
Solution coverage	Extent to which configurations leading to the outcome of interest in the data set correspond to at least one sufficient configuration
Solution consistency	Extent to which all sufficient configurations together are sufficient for the outcome

The analysis for necessary conditions did not reveal any results for high job burnout or low job performance. This means that there is no high- or low-intensity technostressor that always needs to be present for high job burnout or low job performance to occur (Appendix C). The results reveal that job burnout occurs when all technostressors are of high intensity (C1) or when all are of high intensity except techno-uncertainty (C2), techno-complexity (C3), or techno-invasion (C4), each of which may be of low intensity. Low job performance arises when all technostressors are of high intensity (C5).

Post Hoc Analyses

Investigating Configurations that Lead to Low Job Burnout and High Job Performance

In our main analysis, the results provide initial empirical evidence of interdependencies among technostressors. To reveal further insights into how interdependencies shape job burnout and job performance in a positive way and how organizations can promote positive consequences, we conducted a post hoc analysis. We tested for sufficient configurations that lead to low job burnout and high job performance and used the same fsQCA protocol (Appendix C). This procedure revealed one sufficient configuration for low job burnout (C1_low) and five sufficient configurations for high job performance (C2_low - C6_low) (Figure 3).

By comparing the intersection (Park et al., 2017) of the results for low job burnout and high job performance with the main analysis, we attained an understanding of the beneficial and nonbeneficial effects of each configuration. C2_low, C3_low, and C4_low all lead to high job performance but do not lead to high job burnout (Figure 3). These configurations are beneficial for job performance and do not have nonbeneficial consequences in terms of high job burnout. However, C5_low (Figure 3) is equivalent to C4 in the main analysis (Figure 2), and C6_low (Figure 3) is equivalent to C3 in the main analysis (Figure 2). Thus, these two configurations lead to both high job performance and high job burnout and are beneficial in terms of job performance but not job burnout. We found no configuration that leads to both high job performance and low job burnout.

The Mediating Effect of Job Burnout

Research suggests the possibility of an indirect effect of technostressor configurations on behavioral technostrain by way of psychological technostrain, in the sense that high job burnout can mediate the influence of technostressors on low job performance (Tarafdar et al., 2010).

To probe the implied mediation, we performed a two-step fsQCA (Maier et al., 2021) to examine whether there are configurations of technostressors that lead to low job performance and are mediated by job burnout (Appendix D). The results show that both high and low job burnout mediate the configurations of technostressors that lead to low job performance (Figure 4).

The raw coverage values reveal that the configuration of the five high-intensity technostressors is most commonly mediated by high job burnout (coverage: 0.81) and less commonly mediated by low job burnout (coverage: 0.28). The consistency scores are almost equal, indicating that both high and low job burnout are equally suited as mediating conditions.

Mapping of QCA Results with the Three Types of Interdependencies

Based on our fsQCA main analysis as well as our post hoc analyses, we reveal how configurations of interdependent technostressors lead to technostrain. Given these insights, we map the fsQCA results with our theorized interdependencies among the technostressors. Based on the existing literature (Fiss et al., 2013) and our own extensions, we self-developed formulas to apply to our fsQCA results and uncovered empirical evidence of complementarity, contingency, and substitution (Table 4).

Technostressors A and B are *complementary* in a mathematical sense if the technostrain evoked by technostressor A is greater if technostressor B is of high intensity than if technostressor B is of low intensity. Our QCA results in the main analysis (Figure 2) reveal that techno-overload and techno-insecurity have high intensity in all sufficient configurations, which might be due to complementarity among techno-overload and techno-insecurity. Therefore, we tested for complementarity among these two technostressors, i.e., techno-overload (A) and techno-insecurity (B), calculating the respective consistency scores (V). The QCA literature suggests using consistency scores (V) as the metric for comparing the level of the outcomes (Fiss et al., 2013), i.e., technostrain evoked by technostressor A in combination with high-intensity technostressor B versus in combination with low-intensity technostressor B (~B). The results reveal that $V(A \bullet B) - (\sim A \bullet B) = 0.32$, which is greater than $V(A \bullet \sim B) - (\sim A \bullet \sim B) = 0.15$. Thus, the consistency scores support complementarity among techno-overload and techno-insecurity.

Condition \ Configuration	Low job burnout	High job performance				
	C1_low	C2_low	C3_low	C4_low	C5_low	C6_low
Techno-overload	○	○	●	○	●	●
Techno-invasion	○	○	○	●	○	●
Techno-complexity	○	○	○	○	●	○
Techno-insecurity	○	○	○	○	●	●
Techno-uncertainty	○	●	●	●	●	●
Raw/unique/solution coverage	0.40	0.36	0.26	0.22	0.18	0.18
Consistency/solution consistency	0.85	0.86	0.88	0.90	0.92	0.91
Solution coverage (minimized solution)	0.40	0.68				
Solution consistency (minimized solution)	0.85	0.86				

Notes: ● = high intensity, ○ = low intensity, C = configuration

Figure 3. Configurations Leading to Low Job Burnout and High Job Performance

Condition \ Configuration	Low job performance	
	C1_med	C2_med
Outcome-enabling conditions		
Techno-overload	●	●
Techno-invasion	●	●
Techno-complexity	●	●
Techno-insecurity	●	●
Techno-uncertainty	●	●
Mediating condition		
Job burnout	●	○
Raw/unique/solution coverage	0.81	0.28
Consistency/solution consistency	0.96	1.00
Solution coverage (minimized solution)	0.92	
Solution consistency (minimized solution)	0.96	

Notes: ● = high intensity, ○ = low intensity, C = configuration

Figure 4. Configurations of the Two Step fsQCA

Table 4. Mapping of QCA Results with the Three Types of Interdependencies		
Interdependency	**Description**	**Formula***
Complementarity	Complementarity implies that technostressors mutually enhance their effects on technostrain.	Based on Fiss et al. (2013) Technostressor A and technostressor B are complementary if: V(A•B) - V(~A•B) > V(A•~B) - V(~A•~B)
Contingency	Contingency arises when the effect of technostressors on technostrain is only felt in the presence of another technostressor of high intensity.	Self-developed Technostressors A, C, D, and E are contingent upon the intensity of technostressor B if: Outcome(A•B•C•D•E) ≠ Outcome(A•~B•C•D•E)
Substitution	Substitution implies that the high intensities of technostressors offset the low intensity of another technostressor.	Adjusted from Fiss et al. (2013) Technostressors are substitutable if: V(A•~B•C•D•E) ≥ V(A•B•C•D•E)

Note: A, B, C, D, E = high-intensity technostressors; ~A, ~B, ~C, ~D, ~E = low-intensity technostressors; V = consistency; Outcome = high or low technostrain. *The formulas are examples: they are valid for configurations of high- and low-intensity technostressors other than the ones in the example formulas.

From our own theorizing, we derive that *contingency* arises if a configuration of technostressors only leads to high technostrain when another technostressor is also of high intensity. Comparing the results of our analysis that lead to high technostrain (Figure 2) and low technostrain (Figure 3) reveals contingency. For instance, employees exhibit *high* job performance when all technostressors except techno-invasion (~B) are of high intensity (Outcome(A•~B•C•D•E); C5_low). However, if this fifth technostressor, i.e., techno-invasion, is also of high intensity, the outcome changes and employees exhibit *low* job performance (Outcome(A•B•C•D•E); C5).

Turning to *substitution*, technostressors are substitutable if a configuration X that contains at least one low-intensity technostressor can have an equal or even stronger effect on technostrain than a configuration Y that consists of five high-intensity technostressors. In the configurational sense, substitution is not about *one* technostressor substituting for a single other technostressor but concerns *combinations* of high-intensity technostressors substituting for another technostressor. Looking at the configurations leading to high job burnout that contain a low-intensity technostressor (Figure 2, C1-C4), we see that the consistency scores (V) of C2 (0.94), C3 (0.92), and C4 (0.94) are higher than the consistency score (V) of C1 (0.91), where all technostressors are of high intensity. For instance, low-intensity techno-invasion (~B) in combination with high-intensity techno-overload (A), techno-complexity (C), techno-insecurity (D), and techno-uncertainty (E) has a higher consistency score than the configuration in which all technostressors are of high intensity (C1). In sum, our QCA results provide evidence for all three types of interdependencies (Table 4).

Propositions

We used these empirical results to inform five propositions (P1-P5) for future research interested in exploring the interdependencies among the technostressor effects that lead to technostrain. We base our propositions on our initial configurational theorizing (Furnari et al., 2021) and use them to contextualize complementarity, contingency, and substitution to the topic of technostress.

In line with the aggregate approach (Maier et al., 2019; Srivastava et al., 2015), our results suggest that employees who experience all five technostressors at high intensity react to that situation in two ways: by experiencing job burnout and low job performance. We propose that, together, the five high-intensity technostressors drain one's energy and draw from the same resources. High-intensity technostressors can also exacerbate the effects of each other—for example, when the *complementarity* between techno-overload and techno-uncertainty leads to even stronger job burnout. The five high-intensity technostressors lead employees to experience high job burnout because this configuration depletes resources and leads to fatigue regarding IT use. At the same time, employees must invest time and energy to adapt to the different high-intensity technostressors, causing them to feel demotivated and leaving them less time to accomplish their regular work tasks, eventually resulting in low job performance. Therefore, according to this logic, we propose:

P1: *Employees experience high job burnout and demonstrate low job performance when the intensity of all five technostressors is high.*

In considering the possibility of a causal relationship between high job burnout and low job performance, our investigation of the configurations leading to high job burnout and low job performance suggests an interplay between the psychological and behavioral consequences of technostressors. We argue that employees who experience job burnout are less likely to invest the limited resources they have into completing their work tasks and duties and instead maintain a protective, defensive position (Hobfoll, 1989). Therefore, the high job burnout that employees experience when the five technostressors are of high intensity leads to low performance at work (Figure 4, C1_med). Thus, we propose:

P2: *High job burnout mediates the five high-intense technostressors so that they lead to low job performance.*

Our findings suggest that high job burnout does not require each of the technostressors to manifest high intensity. We found that multiple configurations, which include different combinations of high- and low-intensity technostressors, lead to high job burnout. All configurations leading to high job burnout consist of high-intensity techno-overload and techno-insecurity, although they alone are not sufficient to lead to high job burnout. However, as long as all other technostressors are of high intensity, techno-uncertainty (Figure 2, C2) *or* techno-complexity (Figure 2, C3) *or* techno-invasion (Figure 2, C4) may be of low intensity and still lead to job burnout because these low-intensity technostressors are essential components of configurations that deplete individual resources. Thus, combinations of high-intensity technostressors can *substitute* for a low-intensity technostressor, leading to job burnout. Configurations in which all technostressors other than techno-uncertainty, techno-complexity, or techno-invasion are of high intensity can lead to job burnout just as well as configurations in which all technostressors are of high intensity. Therefore, we propose:

P3: *Employees experience high job burnout even when* ***(a)*** *techno-uncertainty or* ***(b)*** *techno-complexity or* ***(c)*** *techno-invasion is of low intensity as long as all other technostressors in the configuration are of high intensity.*

The post hoc findings on low technostrain suggest that employees may still exhibit high job performance even when some technostressors are of high intensity, which is in line with recent research on the positive aspects of technostressors (Stich et al., 2019). We found empirical indications for the buffer hypothesis (Bakker & Demerouti, 2007), which implies that in the context of technostress, low-intensity technostressors can buffer the impact of other high-intensity technostressors on technostrain. For example, enough family or personal time for recovery (low-intensity techno-invasion, Figure 3, C5_low) can buffer the effect of other high-intensity technostressors. Adequate personal time may increase motivation (Bakker & Demerouti, 2007) and enable performance protection strategies (Hockey, 1997), such as increasing subjective effort and mobilizing activation. Therefore, we propose:

P4: *Employees continue to exhibit high job performance even when up to four technostressors are of high intensity.*

Because of *contingency* (Furnari et al., 2021) among technostressors, employees only perform at high levels in the context of high-intensity technostressors if techno-invasion (Figure 3, C5_low) or techno-complexity (Figure 3, C6_low) is of low intensity. Whether employees exhibit high or low job performance when facing high-intensity technostressors depends on the intensity of either techno-invasion or techno-complexity. We found that employees can still exhibit high job performance in the face of high-intensity techno-overload, techno-complexity, techno-insecurity, and techno-uncertainty as long as *techno-invasion* is of low intensity (Figure 3, C5_low); similarly, we found that employees can still exhibit high job performance in the face of high-intensity techno-overload, techno-invasion, techno-insecurity, and techno-uncertainty as long as *techno-complexity* is of low intensity (Figure 3, C6_low). In both of these configurations, if the fifth technostressor, i.e., techno-invasion or techno-complexity, is also of high intensity (Figure 2, C5), job performance suffers. Low-intensity techno-invasion or techno-complexity can serve as a buffer and enable performance protection strategies (Hockey, 1997). Accordingly, we propose:

P5: *An increase in the intensity of* ***(a)*** *techno-invasion or* ***(b)*** *techno-complexity leads to a change from high job performance to low job performance when the other four technostressors are of high intensity.*

Discussion

To understand how interdependencies among technostressors lead to technostrain, we used a configurational approach to identify the configurations of high- and low-intensity technostressors that lead to high job burnout and low job performance. We draw on the insights we gained to articulate the *what, how,* and *why* of interdependencies among technostressors that lead to technostrain.

Theoretical Contributions

We extend technostress work by offering insights into *what* implications the varying intensities of individual technostressors within configurations have. It is well established that high-intensity individual technostressors

(Galluch et al., 2015) or a high-intensity aggregate technostressor construct (Tarafdar et al., 2015) leads to high technostrain. We show that configurations comprised of both high- and low-intensity technostressors can also lead to technostrain. We contribute by revealing the overdetermination (Furnari et al., 2021) of technostressors leading to high job burnout in existing technostress research, meaning that the extant research suggests that more high-intensity technostressors are necessary to lead to high job burnout than are actually necessary. We show that all technostressors need not be of high intensity to lead to high job burnout; rather, we found that a subset of high-intensity technostressors can have *complementary* effects and are therefore sufficient to lead to high job burnout.

Beyond that, we reveal that because of *substitution*, different configurations, including those that contain low-intensity technostressors, have an equivalent impact on high job burnout. This finding complements the literature by providing insights into *what* leads to technostrain for different employees or for one employee in different situations. In fact, one employee may experience high technostrain in different situations or from different configurations of technostressors than other employees.

By considering the relative impact of technostressors, our work provides insight into *how* interdependencies among the effects of technostressors lead to technostrain (Ayyagari et al., 2011; Chen & Karahanna, 2018). We confirm that three types of interdependencies—complementarity, contingency, and substitution—result in four configurations of technostressors that lead to technostrain. By illustrating that there are many different paths to technostrain, our work offers insight into why organizational interventions designed for individual technostressors may fail to mitigate the impact of technostressors by failing to account for the interdependencies among technostressors on employee well-being and job performance. In addition, the results of our post hoc analysis on low technostrain caused us to reconsider the notion of high-intensity technostressors and revealed that their adverse effects are *contingent* upon the intensity of other technostressors. We show that high-intensity technostressors do not necessarily lead to high technostrain and may be well-tolerated by employees. In fact, configurations of high-intensity together with low-intensity technostressors can even lead to low technostrain and high job performance.

When users perceive technostressors, they may respond by exhibiting multiple manifestations of technostrain (Fischer et al., 2021; Tarafdar et al., 2019). Our two-step fsQCA reveals differences as well as interdependencies among the two manifestations of technostrain, i.e., *why* employees experience high job burnout versus low job performance. Employees who report high intensity of all technostressors are likely to experience high job burnout as a state before then exhibiting low job performance because their resources have been depleted by their high levels of job burnout. Our research shows that high job burnout and low job performance result from different mechanisms, meaning that it is necessary to differentiate between different manifestations of technostrain. High job burnout results from drawing excessively from energy resources, resulting in fatigue and exhaustion, which can be caused by fewer high-intensity technostressors than low job performance (compare C2-4 with C5 in Figure 2). Low job performance results from a loss of motivation and engagement in the work (Bakker & Demerouti, 2007), but job performance may remain high even when employees experience high job burnout. If only some technostressors are of high intensity, employees may be able to maintain high job performance.

Further, a conflict may exist between different manifestations of technostrain because configurations of high- and low-intensity technostressors can be beneficial for one manifestation of technostrain but nonbeneficial for another manifestation. For instance, the same configuration, such as all high-intensity technostressors except techno-invasion, which has a low intensity, can lead to high job performance (C5_low) and also to high job burnout (C4). These findings suggest that technostress mitigation research needs to account for the possible side effects of technostressor configurations and highlight the need to simultaneously investigate multiple manifestations of technostrain, e.g., psychological and behavioral.

Implications for Practice

For practice, we derive three recommendations for the assessment and mitigation of technostressors and technostrain in organizational contexts.

Implement interventions driven by a profound assessment of multiple technostressors: Our findings imply that employees, executives, and health managers consider *multiple* technostressors to reduce technostrain. Focusing on one technostressor, for instance techno-invasion, by avoiding sending employees emails outside of work hours—is unlikely to mitigate job burnout. If other technostressors remain at a high intensity, these technostressors alone can be sufficient to lead to high job burnout (substitution) (Figure 2, C4), especially if these remaining technostressors mutually reinforce their effects (complementarity). Thus, managers must carefully assess which technostressors employees are facing and match them to (a combination of) relevant interventions. To reduce high job burnout, interventions should be directed at the many *different paths,* i.e., configurations that can lead to high job burnout.

Be aware that small changes in technostressors can make a big difference: Up to four high-intensity technostressors can be tolerated by employees in terms of job performance as long as a specific technostressor is of low intensity. However, if only one technostressor changes, such as employees feeling the need to be reachable even outside of business hours due to an important project (high-intensity techno-invasion), job performance can suddenly suffer (contingency). In contrast, if managers mitigate this specific technostressor, job performance can improve despite other technostressors remaining at a high intensity. For job burnout, managers may need to initiate more profound changes, given that employees experience job burnout even in the face of fewer high-intensity technostressors.

Do not think you are safe just because employees are performing at a high level: High job burnout can be caused by fewer high-intensity technostressors and can be experienced as a first state before leading to low job performance. Therefore, managers should be sensitive to the fact that an employee may suffer from high job burnout while also being a top performer; thus, improved job performance after introducing technostress mitigation measures does not necessarily mean that technostrain is no longer an issue for employees.

Limitations

We used self-reported data to assess technostrain in the form of high job burnout and low job performance. While our work is consistent with perceptual, empirical technostress research (Ayyagari et al., 2011), objective measures of technostrain (Galluch et al., 2015) may suggest additional configurations of technostressors. Moreover, our study focused on five widely known work-relevant technostressors (Ragu-Nathan et al., 2008). Further work is needed to investigate additional technostressors (Fischer et al., 2021), such as interruptions due to IT (Addas & Pinsonneault, 2018), unreliability (Riedl et al., 2012), and context-specific technostressors (Maier et al., 2022). Finally, our two-wave sampling strategy assessed technostressors in the first wave and technostrain in the second wave. While we confirmed that no IS-related changes took place in the organization between the two waves of data collection that could have induced a change in technostress perception, it is still possible that some participants may have changed their perceptions of technostressors during data collection.

Future Research

Our research paves the way for five research avenues on the interdependencies of technostressors and their impact on the development of technostrain.

Considering interdependencies among challenge technostressors and hindrance technostressors in configurations: Our work reveals interdependencies among well-known "hindrance technostressors." Hindrance technostressors create negative outcomes and are appraised by users as threatening. Recent IS research has also drawn attention to "challenge technostressors" that can create positive outcomes, such as richer IS use through the fostering of personal growth (Benlian, 2020; Califf et al., 2020; Maier et al., 2021). Knowledge from the broader stress literature suggests that challenge and hindrance stressors are not mutually exclusive but interdependent, as one situation can be perceived as both a challenge and a hindrance (Prem et al., 2017). We therefore suggest future research on the interdependencies among hindrance and challenge technostressors and how their configurations impact users. These investigations could reveal further instances where high-intensity technostressors create beneficial outcomes in terms of job performance and identify indications of nonlinearity among technostressors and technostrain. For instance, the negative impacts of high-intensity hindrance technostressors on job performance could become positive and actually improve job performance when combined with specific challenge technostressors.

Studying configurations of technostressors relevant in the other IS use contexts: Our research focuses on work-related technostressors. It is possible that configurations of technostressors have different implications in private contexts for technology use, such as the personal use of IS at home or for fun (Salo et al., 2019). Recent work has suggested that users interact differently with Facebook, TikTok, or Instagram than with workplace technologies, resulting in specific technostressors in the private context (Maier et al., 2022). Future work focusing on a contextualized understanding of which configurations are most relevant to specific domains would yield much theoretical and applied understanding.

Revealing specific types of interdependencies among the effects of distinct technostressors: Our work explains that interdependencies underlie configurations of technostressors that lead to technostrain and provides initial empirical evidence on the three types of interdependencies. Future research could seek to realize a richer understanding of the interdependencies among technostressors. To do so, we believe a qualitative-quantitative mixed-methods study would be necessary (Venkatesh et al., 2013). Qualitative interviews can reveal inductive insights resulting in specific propositions about which types of interdependencies can be found among which technostressors. This could then be tested using a quantitative survey. This approach would enable researchers to, for instance, identify complementarity (e.g., techno-overload and techno-complexity mutually exacerbating each other's effects because they both demand time resources) for multiple specific technostressors.

Considering configurations of technostressors leading to short-term vs. long-term consequences: By focusing on high job burnout and low job performance, our work directs attention to the medium- and long-term consequences of technostressors. However, technostressors can also lead to immediate short-term consequences such as negative affect (Benlian, 2020) or acute increases in stress hormones (Galluch et al., 2015). Future quantitative longitudinal research investigating which configurations of technostressors result in short-term consequences could enhance our understanding of how to detect and prevent technostrain in its early stages.

Revealing effective strategies to mitigate the configurations of technostressors that lead to technostrain: We reveal which configurations are responsible for technostrain. While existing IS literature has focused on coping strategies (Pirkkalainen et al., 2019; Salo et al., 2020) to explain how users adapt to technostressors, these studies have left the interdependencies among technostressors unexamined. Future research could develop and test coping strategies and managerial interventions, e.g., through a pre-post intervention study design, which would be useful for mitigating the four configurations that lead to technostrain identified here.

Conclusion

Technostress is pervasive across organizations. In this study, we demonstrate how configurations of interdependent technostressors lead employees to experience high job burnout or low job performance. Using fsQCA to analyze data gathered in a two-wave study, we identify four configurations of high- and low-intensity technostressors that lead to technostrain. These findings confirm that three specific types of interdependencies exist among technostressors (complementarity, contingency, and substitution) and highlight the importance of studying configurations of high- and low-intensity technostressors to understand, explain, and predict the development of the negative consequences of technostressors. Moreover, for practitioners, our findings demonstrate that developing effective preventive measures requires a holistic understanding of the technostressors that cause technostrain in the workplace.

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References

Addas, S., & Pinsonneault, A. (2018). E-mail interruptions and individual performance: Is there a silver lining? *MIS Quarterly*, *42*(2), 381-405. https://doi.org/10.25300/MISQ/2018/13157

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

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

Benlian, A. (2020). A daily field investigation of technology-driven stress spillovers from work to home. *MIS Quarterly*, *44*(3), 1259-1300. https://doi.org/10.25300/MISQ/2020/14911

Bertalanffy, L. von. (1975). General system theory. In D. Ruben & J. Y. Kim (Eds.), *General Systems Theory and human communication* (pp. 6-20).. Hayden.

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

Carmines, E. G., & Zeller, R. A. (2008). *Reliability and validity assessment*. SAGE.

Chandra, S., Shirish, A., & Srivastava, S. C. (2019). Does technostress inhibit employee innovation? Examining the linear and curvilinear influence of technostress creators. *Communications of the Association for Information Systems*, *44*(1), 299-331. https://doi.org/10.17705/1CAIS.04419

Chatterjee, S., Sarker, S., Lee, M. J., Xiao, X., & Elbanna, A. (2021). A possible conceptualization of the information systems (IS) artifact: A general systems theory perspective. *Information Systems Journal*, *31*(4), 550-578. https://doi.org/10.1111/isj.12320

Chen, A., & Karahanna, E. (2018). Life interrupted: The effects of technology-mediated work interruptions on work and nonwork outcomes. *MIS Quarterly*, *42*(4), 1023-1042. https://doi.org/10.25300/MISQ/2018/13631

Dușa, A. (2018). *QCA with R: A comprehensive resource*. Springer.

Fischer, T., Reuter, M., & Riedl, R. (2021). The digital stressors scale: Development and validation of a new survey instrument to measure digital stress perceptions in the workplace context. *Frontiers in Psychology*, *12*, Article 607598. https://doi.org/10.3389/fpsyg.2021.607598

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, *54*(2), 393-420. https://doi.org/10.5465/amj.2011.60263120

Fiss, P. C., Sharapov, D., & Cronqvist, L. (2013). Opposites attract? Opportunities and challenges for integrating large-N QCA and econometric analysis. *Political Research Quarterly*, *66*(1), 191-198. https://doi.org/10.1177/1065912912468269e

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Furnari, S., Crilly, D., Misangyi, V. F., Greckhamer, T., Fiss, P. C., & Aguilera, R. (2021). Capturing causal complexity: Heuristics for configurational theorizing. *Academy of Management Review*, *46*(4), 778-799. https://doi.org/10.5465/amr.2019.0298

Galluch, P., Grover, V., & 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. https://doi.org/10.17705/1jais.00387

Greckhamer, T., Furnari, S., Fiss, P. C., & Aguilera, R. V. (2018). Studying configurations with qualitative comparative analysis: Best practices in strategy and organization research. *Strategic Organization*, *16*(4), 482-495. https://doi.org/10.1177/1476127018786487

Hobfoll, S. E. (1989). Conservation of Resources: A new attempt at conceptualizing stress. *Amercian Psychologist*, *44*(3), 513-524. https://doi.org/10.1037/0003-066X.44.3.513

Hockey, G. R. J. (1997). Compensatory control in the regulation of human performance under stress and high workload: A cognitive-energetical framework. *Biological Psychology*, *45*(1-3), 73-93. https://doi.org/10.1016/S0301-0511(96)05223-4

Karasek, R. A. (1979). Job demands, job decision latitude, and mental strain: Implications for job redesign. *Administrative Science Quarterly*, *24*(2), 285-308. https://doi.org/10.2307/2392498

Khedhaouria, A., & Cucchi, A. (2019). Technostress creators, personality traits, and job burnout: A fuzzy-set configurational analysis. *Journal of Business Research*, *101*, 349-361. https://doi.org/10.1016/j.jbusres.2019.04.029

Kock, N. (2015). Common Method Bias in PLS-SEM. *International Journal of E-Collaboration*, *11*(4), 1-10. https://doi.org/10.4018/ijec.2015100101

Liu, Y., Mezei, J., Kostakos, V., & Li, H. (2017). Applying configurational analysis to IS behavioural research: A methodological alternative for modelling combinatorial complexities. *Information Systems Journal*, *27*(1), 59-89. https://doi.org/10.1111/isj.12094

Maier, C., Laumer, S., Tarafdar, M., Mattke, J., Reis, L., & Weitzel, T. (2021). Challenge and hindrance IS use stressors and appraisals: Explaining contrarian associations in post-acceptance IS use behavior. *Journal of the Association for Information Systems*, *22*(6), 1590-1624. https://doi.org/10.17705/1jais.00709

Maier, C., Laumer, S., Thatcher, J. B., Wirth, J., & Weitzel, T. (2022). Trial-period technostress: A conceptual definition and mixed-methods investigation. *Information Systems Research*, *33*(2), 489-514. https://doi.org/10.1287/isre.2021.1047

Maier, C., Laumer, S., Wirth, J., & Weitzel, T. (2019). Technostress and the hierarchical levels of personality: a two-wave study with multiple data samples. *European Journal of Information Systems*, *62*(1), 1-27. https://doi.org/10.1080/0960085X.2019.1614739

Mattke, J., Maier, C., Weitzel, T., E. Gerow, J., & B. Thatcher, J. (2022). Qualitative Comparative Analysis (QCA) in Information Systems research: Status quo, guidelines, and future directions. *Communications of the Association for Information Systems*, *50*, Article 8, 208-240. https://doi.org/10.17705/1CAIS.05008

Misangyi, V. F., Greckhamer, T., Furnari, S., Fiss, P. C., Crilly, D., & Aguilera, R. (2017). Embracing causal complexity: The emergence of a neo-configurational perspective. *Journal of Management*, *43*(1), 255-282. https://doi.org/10.1177/0149206316679252

Mithas, S., Park, Y., & Saldanha, T. (2020). Digital strategy and discretionary expenditures: Novel insights from a configurational approach. *Academy of Management Proceedings*. https://doi.org/10.5465/AMBPP.2020.18464abstract

Mithas, S., Xue, L., Huang, N., & Burton-Jones, A. (2022). Editor's comments: Causality meets diversity in information systems research. *MIS Quarterly*, *46*(3), i-xvii.

Nastjuk, I., Trang, S., Grummeck-Braamt, J.-V., Adam, M. T. P., & Tarafdar, M. (2023). Integrating and synthesising technostress research: A meta-analysis on technostress creators, outcomes, and IS usage contexts. *European Journal of Information Systems.* Advance online publication. https://doi.org/10.1080/0960085X.2022.2154712

Nunnally, J. (1978). *Psychometric methods*. McGraw-Hill.

Ordanini, A., Parasuraman, A., & Rubera, G. (2014). When the recipe is more important than the ingredients. *Journal of Service Research*, *17*(2), 134-149. https://doi.org/10.1177/1094670513513337

Park, Y., Fiss, P. C., & El Sawy, O. A. (2020). Theorizing the multiplicity of digital phenomena: The ecology of configurations, causal recipes, and guidelines for applying QCA. *MIS Quarterly*, *44*(4), 1493-1520. https://doi.org/10.2139/ssrn.4158044

Park, Y., Sawy, O. E., & Fiss, P. (2017). The role of business intelligence and communication technologies in organizational agility: A configurational approach. *Journal of the Association for Information Systems*, *18*(9), 648-686. https://doi.org/10.17705/1jais.00467

Pflügner, K., Maier, C., Mattke, J., & Weitzel, T. (2021). Personality profiles that put users at risk of perceiving technostress: A qualitative comparative analysis with the Big Five personality traits. *Business & Information Systems Engineering*, *63*(4), 389-402. https://doi.org/10.1007/s12599-020-00668-7

Pirkkalainen, H., Salo, M., Tarafdar, M., & Makkonen, M. (2019). Deliberate or instinctive? Proactive and reactive coping for technostress. *Journal of Management Information Systems*, *36*(4), 1179-1212. https://doi.org/10.1080/07421222.2019.1661092

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management*, *12*(4), 531-544. https://doi.org/10.1177/014920638601200408

Prem, R., Ohly, S., Kubicek, B., & Korunka, C. (2017). Thriving on challenge stressors? Exploring time pressure and learning demands as antecedents of thriving at work. *Journal of Organizational Behavior*, *38*(1), 108-123. https://doi.org/10.1002/job.2115

Ragin, C. C. (2014). *The comparative method: Moving beyond qualitative and quantitative strategies*. University of California Press.

Ragin, C. C., & Sonnett, J. (2005). Between complexity and parsimony: Limited diversity, counterfactual cases, and comparative analysis. In S. Kropp & M. Minkenberg (Eds.), *Vergleichen in der Politikwissenschaft* (pp. 180-197). Springer. https://doi.org/10.1007/978-3-322-80441-9_9

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

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

Salo, M., Makkonen, M., & Hekkala, R. (2020). The interplay of IT users' coping strategies: Uncovering momentary emotional load, routes and sequences. *MIS Quarterly*, *44*(3), 1143-1175. https://doi.org/10.25300/MISQ/2020/15610

Salo, M., Pirkkalainen, H., & Koskelainen, T. (2019). Technostress and social networking services: Explaining users' concentration, sleep, identity, and social relation problems. *Information Systems Journal*, *29*(2), 408-435.

Schneider, C. Q., & Wagemann, C. (2006). Reducing complexity in Qualitative Comparative Analysis (QCA): Remote and proximate factors and the consolidation of democracy. *European Journal of Political Research*, *45*(5), 751-786. https://doi.org/10.1111/j.1475-6765.2006.00635.x

Schneider, C. Q., & Wagemann, C. (2012). *Set-theoretic methods for the social sciences: A guide to qualitative comparative analysis*. Cambridge University Press.

Sharma, Yetton, & Crawford (2009). Estimating the effect of common method variance: The method—method pair technique with an illustration from TAM research. *MIS Quarterly*, *33*(3), 473. https://doi.org/10.2307/20650305

Srivastava, S. C., Chandra, S., & Shirish, A. (2015). Technostress creators and job outcomes: Theorising the moderating influence of personality traits. *Information Systems Journal*, *25*(4), 355-401. https://doi.org/10.1111/isj.12067

Stich, J.-F., Tarafdar, M., Stacey, P., & Cooper, C. (2019). Appraisal of email use as a source of workplace stress: A person-environment fit approach. *Journal of the Association for Information Systems*, *20*(2), 132-160. https://doi.org/10.17705/1jais.00531

Tams, S., Thatcher, J. B., & Grover, V. (2018). Concentration, competence, confidence, and capture: An experimental study of age, interruption-based technostress, and task performance. *Journal of the Association for Information Systems*, *19*(9), 857-908. https://doi.org/10.17705/1jais.00511

Tarafdar, M., Cooper, C. L., & 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. https://doi.org/10.1111/isj.12169

Tarafdar, M., Pullins, E. B., & Ragu-Nathan, T. S. (2015). Technostress: Negative effect on performance and possible mitigations. *Information Systems Journal*, *25*(2), 103-132. https://doi.org/10.1111/isj.12042

Tarafdar, M., Tu, Q., & Ragu-Nathan, T. S. (2010). Impact of technostress on end-user satisfaction and performance. *Journal of Management Information Systems*, *27*(3), 303-334. https://doi.org/10.2753/MIS0742-1222270311

Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, *37*(1), 21-54.

Weinert, C., Maier, C., Laumer, S., & Weitzel, T. (2022). Repeated IT interruption: Habituation and sensitization of user responses. *Journal of Management Information Systems*, *39*(1), 187-217. https://doi.org/10.1080/07421222.2021.2023411

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Appendix A

Measures

Table A1. Items, Measures, and Loadings

Construct	Item	Loading
Techno-overload adapted from Ragu-Nathan et al. (2008) Cronbach's α = 0.91	I am forced by this technology to work much faster.	0.835
	I am forced by this technology to do more work than I can handle.	0.901
	I am forced by this technology to work with very tight time schedules.	0.926
	I am forced to change my work habits to adapt to new technologies.	0.824
	I have a higher workload because of increased technology complexity.	0.855
Techno-invasion adapted from Ragu-Nathan et al. (2008) Cronbach's α = 0.85	I spend less time with my family due to this technology.	0.882
	I have to be in touch with my work even during my vacation due to this technology.	0.849
	I have to sacrifice my vacation and weekend time to keep current on new technologies.	0.829
	I feel my personal life is being invaded by this technology.	0.809
Techno-complexity adapted from Ragu-Nathan et al. (2008) Cronbach's α = 0.87	I do not know enough about this technology to handle my job satisfactorily.	0.853
	I need a long time to understand and use new technologies.	0.832
	I do not find enough time to study and upgrade my technology skills.	0.873
	I find new recruits to this organization know more about computer technology than I do.	0.751
	I often find it too complex for me to understand and use new technologies.	0.774
Techno-insecurity adapted from Ragu-Nathan et al. (2008) Cronbach's α = 0.84	I feel constant threat to my job security due to new technologies.	0.849
	I have to constantly update my skills to avoid being replaced. (*removed*)	<0.707
	I am threatened by coworkers with newer technology skills.	0.883
	I do not share my knowledge with my coworkers for fear of being replaced	0.779
	I feel there is less sharing of knowledge among coworkers for fear of being replaced.	0.798
Techno-uncertainty adapted from Ragu-Nathan et al. (2008) Cronbach's α = 0.85	There are always new developments in the technologies we use in our organization.	0.843
	There are constant changes in computer software in our organization.	0.911
	There are constant changes in computer hardware in our organization.	0.919
	There are frequent upgrades in computer networks in our organization.	0.836
Job burnout adapted from Srivastava et al. (2015) Cronbach's α = 0.95	I feel emotionally drained by my work.	0.886
	Working at my job all day long requires a great deal of effort.	0.719
	I feel like my work is breaking me down.	0.894
	I feel frustrated with my work.	0.891
	I feel I work too hard on my job.	0.809
	It stresses me too much to work on my job.	0.912
	I feel like I am at the end of my rope.	0.844
	I feel burned out from my work.	0.891
	I feel used up at the end of the workday	0.820
Job performance adapted from Tarafdar et al. (2010) Cronbach's α = 0.97	Technology helps to improve the quality of my work.	0.946
	Technology helps to improve my productivity.	0.952
	Technology helps me to accomplish more work than would otherwise be possible.	0.929
	Technology helps me to perform my job better.	0.958
	Technology helps me to identify innovative ways of doing my job.	0.960
	Technology helps me to come up with new ideas relating to my job.	0.802

Note: Techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty were measured in the first wave; job burnout and job performance were measured in the second wave.

Appendix B

Measurement Model and Common Method Bias

Our estimates of item reliability, internal consistency reliability, convergent validity, and discriminant validity show that the measures are reliable and valid (Liu et al., 2017) (Tables B1 and B2).

Table B1. Evaluation of the Measurement Model

Quality criterion	Threshold	Evaluation in our study
Item reliability	All loadings of the items must exceed the threshold of 0.707 (Carmines & Zeller, 2008).	One item was below the threshold and was removed, while all other items had loadings higher than the recommended threshold. We repeated the analysis with the item included and the results show that this did not influence the results of our analysis.
Internal consistency reliability	Cronbach's alpha must exceed 0.70 (Nunnally, 1978) and the composite reliability (CR) must exceed 0.70 (Fornell & Larcker, 1981).	The constructs' Cronbach's alpha ranges from 0.80 to 0.90 and their composite reliability (CR) ranges from 0.89 to 0.97 (Table B2).
Convergent validity	The AVE must exceed the threshold of 0.50 (Fornell & Larcker, 1981).	The constructs' average variance extracted (AVE) ranges from 0.68 to 0.86.
Discriminant validity	The square root of the AVE must be greater than the corresponding correlations of the constructs (Fornell & Larcker, 1981). The heterotrait-monotrait (HTMT) must be below 0.85 (Henseler et al. 2014).	The square root of the AVE, which is displayed on the diagonal of the bivariate correlations (Table B2), is greater than the corresponding correlations of the constructs. The HTMT value is 0.79 (techno-complexity and techno-insecurity), below the HTMT 0.85 threshold.

Table B2. Descriptive Statistics, Bivariate Correlations, and Discriminant Validity

Construct	Mean	SD	CR	AVE	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Techno-overload	3.87	1.55	0.94	0.79	**0.89**						
(2) Techno-invasion	3.64	1.62	0.90	0.68	0.60	**0.83**					
(3) Techno-complexity	3.11	1.44	0.91	0.71	0.55	0.45	**0.84**				
(4) Techno-insecurity	3.00	1.47	0.89	0.67	0.51	0.49	0.74	**0.82**			
(5) Techno-uncertainty	4.47	1.61	0.91	0.77	0.45	0.28	0.23	0.36	**0.88**		
(6) Job burnout	3.82	1.71	0.96	0.73	0.44	0.43	0.41	0.41	0.21	**0.85**	
(7) Job performance	4.41	1.83	0.97	0.86	-0.01	0.10	0.30	0.18	-0.31	0.01	**0.93**

Note: The square root of AVE is listed on the diagonal of bivariate correlations; SD = standard deviation; CR = composite reliability; AVE = average variance extracted

Although concerns about common method bias (CMB) are alleviated because the independent and dependent variables were collected on separate surveys, we tested for common method bias (CMB). Harman's single-factor test (Podsakoff & Organ, 1986) revealed that one factor explains less than 39.02% of the variance and is below the threshold of 50%. Moreover, we inspected the bivariate correlations, given that no high (>0.90) bivariate correlations were detected (Table 4) (Sharma et al., 2009). As suggested by existing research, we also conducted a full collinearity test (Kock, 2015). Also, we calculated all our latent constructs' variance inflation factors (VIFs). High VIFs (>3.30) are an indicator for CMB. The highest VIF was 2.70 for techno-complexity. In summary, the three tests indicate that CMB is not an issue in this study.

Appendix C

Analysis of Sufficient Configurations and Necessary technostressors

We took two steps to analyze sufficient configurations (Fiss, 2011). In the first step, with the calibrated data, we consolidated a truth table for high job burnout and another one for low job performance. We covered 79.13% of all possible configurations, showing that a high percentage of configurations are covered, leading to reliable and robust QCA results (Schneider & Wagemann, 2012). In the second step, we reduced the consolidated truth tables for high job burnout and low job performance to sufficient configurations by using three thresholds. We used a frequency threshold of 3.00 (Ordanini et al., 2014; Park et al., 2017), a raw consistency threshold of 0.85 (Liu et al., 2017; Misangyi et al., 2017), and applied the proportional reduction in inconsistency (PRI) of 0.75. The raw consistency threshold refers to the degree of consistency with which the configurations lead to high job burnout or low job performance. The PRI refers to the degree to which a given configuration is insufficient for both the high and low outcomes (Greckhamer et al., 2018). Using the thresholds, we removed 6.62% of the configurations from the analysis, which is well below the maximum of 20% (Greckhamer et al., 2018). As the goal was to comprehend the complexity of technostressors, we did not minimize the solutions and gave complex solutions precedence over the goal of a parsimonious solution (Ragin, 2014). The raw coverage equals the unique coverage and the solution coverage, and the consistency of a sufficient configuration equals the solution consistency. To get an estimate of the relevance of each sufficient configuration, we additionally report the solution coverage and solution consistency of the logically minimized solution (Figure 2, last row).

Beyond accounting for the intensities of technostressors, which was our focus, fsQCA also allowed us to distinguish between core and peripheral conditions, which provide additional details about the strengths of evidence for a causal relationship. We evaluated core conditions by examining the intermediate and parsimonious solution formulas. Core conditions provide strong evidence for a causal relationship with the outcome, whereas peripheral conditions provide relatively weaker evidence for a causal relationship with the outcome (Fiss, 2011). We neither relied on ease nor complicated counterfactual analysis for the intermediate solution because not enough knowledge about configurations of technostressors exists to make reasonable assumptions. To examine the core conditions, we followed the recommendations of previous research (Dușa, 2018; Ragin & Sonnett, 2005) and examined and removed untenable simplifying assumptions to avoid distorting the results. We identified all high-intensity technostressors, in addition to low-intensity techno-uncertainty, as core conditions for high job burnout. This finding indicates that all five high-intensity technostressors as well as low-intensity techno-uncertainty provide strong evidence for a causal relationship with high job burnout. For low job performance, all high-intensity technostressors except high-intensity techno-overload represent core conditions. Thus, four out of five high-intensity technostressors together produce strong evidence for a causal relationship with low job performance.

We tested whether any of the five technostressors are necessary for high job burnout or low job performance, focusing on the consistency and coverage of all high and low technostressors. Consistency captures the extent to which a technostressor is consistently a necessary technostressor, and it must exceed a consistency threshold of 0.90. Coverage assesses the empirical relevance of the technostressors and the coverage threshold is 0.60 (Misangyi et al., 2017). Our findings show values below those thresholds, such that our results reveal no necessary technostressors.

To test the robustness of our results, we performed various sensitivity analyses, as suggested in prior research (Mattke et al., 2022). The results are robust to the selected thresholds, as the frequency threshold can be increased up to 4 for high job burnout and up to 13 for low job performance. The raw consistency is robust up to 0.909 for high job burnout and 0.875 for low job performance. Similarly, the PRI is robust to an increase of up to 0.775 for high job burnout and 0.754 for low job performance. Moreover, the results are robust to changes in the calibration anchors. We tested anchors closer to the point of maximum ambiguity, i.e., the results are robust to 2.50 as the anchor for being fully out of the set, 4 as the point of maximum ambiguity, and 5.50 as the anchor for being fully in the set. The results are also robust to anchors further away from the point of maximum ambiguity, i.e., robust to 1.50 as the anchor for being fully out of the set, 4 as the point of maximum ambiguity, and 6.50 as the anchor for being fully in the set. Finally, we tested the robustness of the adjusted 0.50 fuzzy values and revealed that the results are robust to adding or subtracting a small constant of 0.001. In summary, we can conclude that our results are robust.

Appendix D

Mediation Analysis with a Two-Step fsQCA

We differentiated between outcome-enabling conditions (i.e., technostressors) and the mediating condition (i.e., job burnout) and performed two nested fsQCAs. We first analyzed which configurations of technostressors lead to low job performance. We again used the same calibrated data for the two-step fsQCA, which consisted of two analyses (Maier et al., 2021; Schneider & Wagemann, 2006) and applied the same frequency and consistency thresholds as in the main analysis. The findings reveal one outcome-enabling-sufficient configuration (solution coverage: 0.35, solution consistency: 0.88), i.e., the five high-intensity technostressors (Table D1, Row 1). An outcome-enabling sufficient configuration refers to a configuration of technostressors that always leads to low job performance.

We then considered job burnout as the mediating condition and filtered the entire data set to include only observations that matched the outcome-enabling sufficient configuration. We analyzed which configurations of job burnout are sufficient to enable low job performance with this filtered data set, used the same consistency thresholds as in the main analysis, and set the frequency threshold to 1 (Schneider & Wagemann, 2006) due to the lower number of cases. The results show two mediating-sufficient configurations (Table D1, Row 2), i.e., configurations of job burnout that always lead to low job performance, which are not logically minimized to comprehend the complexity (Ragin, 2014).

Finally, we combined the outcome-enabling-sufficient configuration with the mediating-sufficient configurations into combined-sufficient configurations (Table D1, Row 3). The combined-sufficient configurations show that all technostressors have high intensity and that high job burnout as well as low job burnout mediate the technostressors and lead to low job performance.

Table D1. Summary of the Two Step fsQCA Results

Configuration	Solution	Solution coverage	Solution consistency
Outcome-enabling-sufficient configurations	Techno-overload*Techno-invasion*Techno-complexity*Techno-insecurity*Techno-uncertainty → Low job performance	0.35	0.88
Mediating-sufficient configurations	Job burnout + ~Job burnout → Low job performance	0.84	0.90
Combined-sufficient configurations	Techno-overload*Techno-invasion*Techno-complexity*Techno-insecurity*Techno-uncertainty*Job burnout + Techno-overload*Techno-invasion*Techno-complexity*Techno-insecurity*Techno-uncertainty*~Job burnout → Low job performance.	0.92	0.96

Note: In Boolean expression * means AND, + means OR, ~ means negation, → means sufficient association