Technology, Mind, and Behavior • Technology in a Time of Social Distancing

Virtual Work Communication During a Pandemic—The Moderating Effect of Technology Expertise on Technology Overload

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ABSTRACT

The coronavirus disease (COVID-19) pandemic and its accompanying restrictive measures have led to a sudden digitalization of all areas of work and to many knowledge workers now working entirely from home. Especially, the use of information and communication technologies (ICT) has been associated with negative outcomes such as technology overload. Interacting with technology is dynamic and employees often have to face negative ICT events that are related to the technology's characteristics (e.g., system reliability). In this preregistered study, we aimed to link ICT events with employees' technology overload during a phase of intensive telework. In a daily diary study over the course of 2 weeks, we investigated how ICT events impact technology overload. Additionally, we explored how technology overload as well as professional isolation due to current pandemic-related restrictions impacts employee strain. Multilevel regression modeling was used to explore the described relationships. ICT events were a significant predictor of technology overload and a significant interaction effect of objective technology expertise was found. Technology overload further impacts ICT-related strain. No significant effects were found regarding professional isolation. Gaining a better understanding of the relationship between ICT events, technology overload, and technology expertise during a phase of extensive telework will help to develop training and support for employees to improve their interaction with virtual communication systems during times of social distancing and beyond.

Keywords: virtual work, ICT events, technology overload, professional isolation, expertise

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The coronavirus disease (COVID-19) pandemic has expedited processes of digitalization in the workplace. Employees who have been able to shift their work to home office settings, which is particularly the case for knowledge workers, have been faced with handling many new and diverse digital systems (especially information and communication technologies [ICT]). Although digitalization aims to improve employee performance (Larson & DeChurch, 2020), employees often struggle with handling digital systems (Day et al. (2010, Day et al., 2012; Mitchell & Brynjolfsson, 2017). Even before the onset of restrictive measures relating to the pandemic (e.g., shelter-in-place), virtual work communication has been associated with adverse work-related outcomes (e.g., work overload; Demerouti et al., 2014) and user reactions (e.g., technostress; Ayyagari et al. (2011). For many, work communication has fundamentally changed and will remain virtual for an extended period of time. This includes being socially distanced from colleagues and being limited to virtual work interactions. Findings relating to telework indicate that individuals differ in coping with working from home (Charalampous et al., 2019). Although telework intensity impacts technology-related stress and job satisfaction, individuals who have more experience at virtual work may experience lower technostress (Suh & Lee, 2017).

Furthermore, professional isolation while working from home, which negatively impacts well-being (Bentley et al., 2016), may differ between individuals. Especially differences in the effective use of ICTs (Charalampous et al., 2019) may impact employees' well-being. In light of current developments, it is expected that the intensity of telework will remain high among knowledge workers, and companies may decide to rely on remote work even after restrictions are lifted (Conger, 2020). To better understand how remote work will impact knowledge workers in the future, the present article aims to combine research from work and organizational psychology and human–computer interaction (HCI). We will specifically investigate how events related to the use of ICTs affect employees' technology overload.

Because of the dynamic nature of virtual communication at work (Golden et al., 2008), researchers have pointed out the importance of breaking down specific events related to ICT use (Braukmann et al. (2018); Ganster & Rosen, 2013). In the workplace ICT literature (Braukmann et al. (2018); Day et al. (2010, Day et al., 2012), definitions of these events tend to combine a wide variety of concepts. For instance, definitions of ICT-related events relate to the technical setup of the ICT, such as system characteristics (e.g., system reliability), to interaction behavior (e.g., poor communication between employees via ICTs), to work stressors (e.g., workload), or to aspects of organizational culture or norms (e.g., expectations concerning response availability and speed). In contrast, HCI literature differentiates system characteristics from stressors (such as work overload or invasion of privacy) and highlights that these stressors may mainly result from a misfit between the technology used and the users (person-technology fit framework; Ayyagari et al. (2011; Tarafdar & Wenninger, 2018; Yan et al., 2013). Thus, while often wearing similar labels, definitions of ICT events may slightly differ depending on their theoretical foundation (i.e., HCI or workplace ICT). To further investigate this link between ICT interaction and stressors, the present study focuses on events relating to the system's characteristics that are usually considered negative (e.g., errors), and their effect on technology overload. These ICT events include technical errors, disruptions, and multichannel use (Braukmann et al. (2018)), hassles (e.g., ICT freezes for a few seconds; Day et al. (2010, Day et al., 2012) as well as events relating to ICT reliability (consistent functioning of the ICT; Ayyagari et al. (2011). This approach is in line with prior calls for differentiating technology characteristics and their effects rather than treating technology as a surrogate of various factors and levels (e.g., organizational level; Ayyagari et al. (2011). These negative ICT events vary on a daily basis and can have detrimental effects on employee well-being (Braukmann et al. (2018)). With an increased time spent with ICTs while working from home, it may be assumed that the number of negative ICT events has increased accordingly. However, research on telework has not yet addressed how individuals evaluate these daily negative ICT events.

As the number of systems used and the amount and speed of communication increase, so do employees' processing requirements. An imbalance between employees' processing capabilities and processing requirements has been related to employees experiencing overload (see, e.g., limited capacity model or information overload literature; Eppler & Mengis, 2004; Karr-Wisniewski & Lu, 2010; Lang, 2000). With the current increase in digital communication, employees may experience having too many demands to handle. Karr-Wisniewski & Lu, 2010 extend earlier concepts of information load and describe technology overload as a broader concept relating to individuals experiencing information, communication, and system feature overload while using technology at work. Similar to Ayyagari et al. (2011, the authors argue that the experience of technology overload is a function of the individuals experiencing it, not the technology. To investigate the link between ICT-system use and stress, it is relevant to address environment demands, such as system characteristics, separately from related stress reactions.

Interacting with diverse ICTs and handling large information and communication loads do not affect all individuals equally (Eppler & Mengis, 2004; LaRose et al., 2014), leading to differences in technology-related stress (Ragu-Nathan et al., 2008). Individual differences, such as expertise or feelings of competence, have been described to impact this initial perception of stress creators (Ragu-Nathan et al., 2008) as well as reactions to other technology characteristics, such as a system's reliability (Schaefer et al., 2016). The person-technology-fit framework describes "*how* technology characteristics influence stressors" (Ayyagari et al. (2011, p. 836). According to the model, a misfit between the system's characteristics and the person (e.g., abilities) can increase stressors, which in turn influence strain. "Ultimately, the individual's evaluation of the gap (which will be influenced by individual characteristics) is the precursor to the stressor." (Ayyagari et al. (2011, p. 836).

HCI research indicates that especially individual-level expertise impacts user reactions (e.g., trust or technostress; e.g., Schaefer et al., 2016). The present study will differentiate between objective (OTE) and subjective (STE) technology expertise. OTE describes an objectively measurable experience (e.g., years) in dealing with digital communication systems. On the other hand, STE represents an individual's confidence in dealing with a system (e.g., Peiffer et al., 2020; Ulfert & Scherer, 2020). Although this differentiation has a long tradition in the context of competence measures (e.g., in educational psychology), empirical results differentiating the effects of OTE and STE are still lacking in the context of work. Especially, STE has been shown to strongly impact technology interaction (Ulfert & Scherer, 2020). We argue that, similar to ability (e.g., Ayyagari et al. (2011), expertise influences individuals' evaluation of system characteristics, reducing the person-technology misfit, and therewith the negative effects of ICT events on technology overload. This is relevant, as technology overload can be seen as a work demand (e.g., job demands–resources model; Westerink et al., 2002), which negatively impacts strain (Zapf et al., 2001).

For this registered report,[1] we conducted a daily diary study to understand how employees are affected by negative ICT events and how they differ in dealing with virtual communication in the current situation (see Figure 1). The study contributes to current literature on virtual work and HCI in two ways. First, we investigate how the increase in virtual communication due to remote work affects the experience and individual evaluation of negative ICT events and how this impacts technology overload. Second, we propose to differentiate between OTE and STE as a moderator of this relationship.

> *Hypothesis 1:* Negative ICT events are positively related to daily technology overload.

> *Hypothesis 2a:* Person-level STE moderates the relationship between day-level negative ICT events and technology overload. Specifically, the positive relationship is weaker for individuals high in STE than for individuals low in STE.

> *Hypothesis 2b:* Person-level OTE moderates the relationship between day-level negative ICT events and technology overload. Specifically, the positive relationship is weaker for individuals high in OTE than for individuals low in OTE.

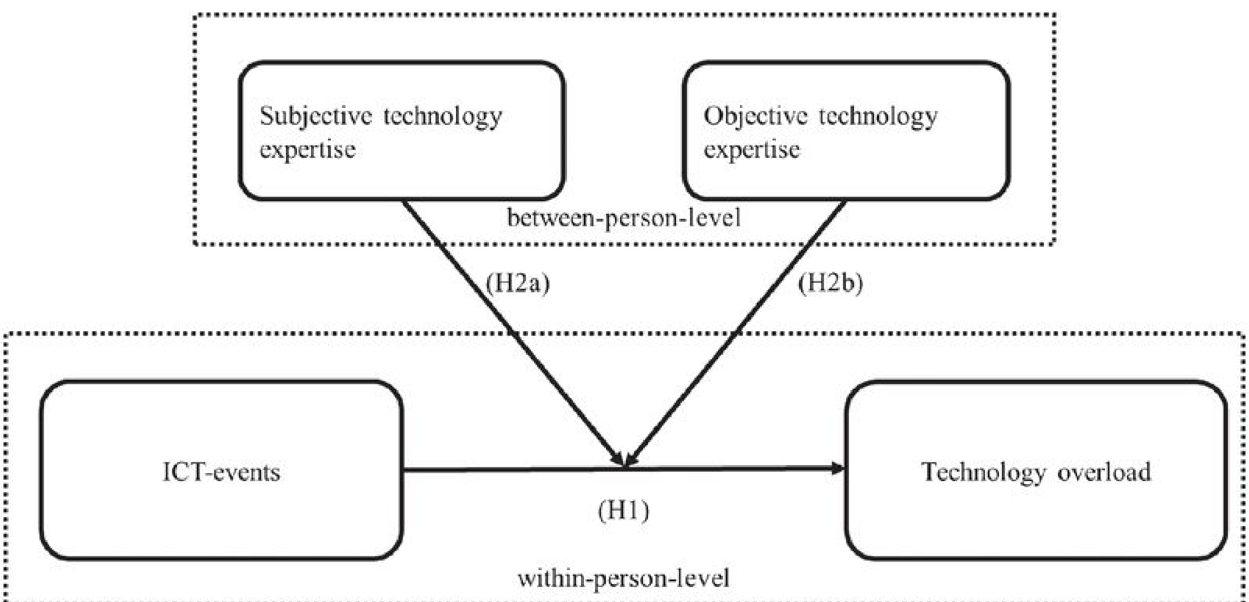

Figure 1
Hypothesized Model

Restrictions relating to social distancing have led many companies to mandate home office for the majority of staff (Conger, 2020). This is an unprecedented situation, as previously (a) most employees were able to choose whether to do telework and (b) in many cases, telework did not take place every day for extended periods of time (Allen et al., 2015). With many companies discussing options for permanent remote work (e.g., Facebook; Conger, 2020), understanding the consequences of extensive telework and professional isolation becomes increasingly important. Professional isolation has previously been described as a major challenge among teleworkers and has been related to low job satisfaction and performance (Golden et al., 2008). At the same time, teleworkers are reported to experience lower levels of professional isolation when digital communication systems are successfully implemented and used (Golden et al., 2008). Professional isolation has thus far not been studied in the context of daily ICT events, expertise, or technology overload. In light of future developments and the expected continuation of telework, we will address the following.

Exploratory Research Question

How do technology overload and professional isolation impact strain in knowledge workers during times of intensive telework?

Method

The design of a 2-week diary study was chosen to analyze the influence of ICT events on technology overload on a within- and a between-person level.[2] This is advantageous because it can be presumed that the results from the daily measures represent the employees' daily work more realistically than one-time measures (Ohly et al., 2010). In particular, ICT events, which might vary from day to day, can be assessed more accurately with daily surveys. The diary study consisted of four different questionnaires (two one-time and two daily), described in the subsequent paragraphs. Before the start of the study, we conducted a cognitive pretest[3] (N = 8) to evaluate the day-level ICT-event and technology overload scales. One item was added to the ICT-event scale based on the participants' feedback.

Participants

The sample for the study was composed of three individual data collections in Germany. Participants for the first two samples were recruited with a flyer via personal contacts and social networks (e.g., LinkedIn, WhatsApp). The third sample was collected in cooperation with an international company working in the beverage and food processing industry. As compensation, ten 50€ vouchers were raffled among all participants. Furthermore, participants could register for short individual feedback regarding their use of ICTs. In terms of study requirements, participants had to be knowledge workers and work mainly from home (minimum 3 days per week). Data collection took place between December 2020 and January 2021 during Germany's second national COVID-19 related lockdown. Because of these circumstances, all participants worked from home full-time during their participation in the study.

In total, 157 subjects participated in the study. Overall, 1,049 daily surveys were collected. As a first step of the data preparation, all empty and insufficient level-1 questionnaires were excluded (154 daily surveys). Afterward, we assessed the daily responses for straightlining (i.e., giving identical ratings to a series of items). Five questionnaires from two participants were identified to have zero variance responses in the ICT events and technology overload items and were thus excluded. Ten participants (and their 34 daily surveys) were excluded because they did not fill out the one-time questionnaire at the beginning of the study. Four participants were excluded because they dropped out during the one-time questionnaire. Further, 10 participants were excluded because they dropped out before finishing the first daily questionnaire. The data preparation resulted in a final sample of 143 participants and 856 daily questionnaires. The final sample consisted of participants between 19 and 66 years of age with an average of 38.55 years ($SD = 10.98$). In total, 120 participants completed the final one-time questionnaire, reducing the total sample size of the additional exploratory analyses by 13.

Apart from those employees working for the cooperating company in the beverage and food processing industry, participants worked in various industries like public services; banks, finance, and assurances; biotech, pharma, chemistry, and medicine; or research and education. As participants were recruited in different waves, the final data set was checked for meaningful differences in the three subsamples ($N_1 = 42$; $N_2 = 13$; $N_3 = 88$). The analysis indicated no significant differences concerning the main variables investigated in the hypotheses. A notable difference was found in the mean age of the subsamples. Further, correlations between age and the main study variables were found. The authors thus decided to include age as a control variable.

Procedure

The entire diary study was conducted online and lasted 2.5 weeks, with 2 weeks during which participants answered daily questionnaires.[4] The study started with a one-time questionnaire that included general information and the informed consent form. Participants were advised to complete it before the start of the daily questionnaires. Afterward, participants received two daily questionnaires on all working days for 2 weeks, leading to a total number of 20 questionnaires. Participants received one more questionnaire at the end of the second study week to conclude the study.

Measures

The study was conducted in German, using validated translations of English scales if available. All questionnaires exclusively available in English were translated and back-translated by three subject-matter experts,[5] using the committee approach (see Cha et al., 2007, for an overview of translation methods).[6] Descriptive statistics and reliabilities of all measures can be found in Table 1.

Table 1

Means, Standard Deviations, and Correlations

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. ICT events (IE)	1.66	0.60	1	.82**	.73**	.65**	.38**	.50**	.36**	.45**	.44**	−.14**	.00	−.11**	.11**	.25**
2. IE: Technical error	1.52	0.66	.87**	1	.48**	.35**	.35**	.34**	.17**	.26**	.42**	−.07*	−.03	−.16**	.07**	.16**
3. IE: Reliability	2.23	1.15	.78**	.57**	1	.11**	.23**	.16**	.05	.09*	.28**	−.06	.03	−.04	.05	.02
4. IE: Interruptions	2.16	0.83	.70**	.50**	.21*	1	.12**	.63**	.60**	66**	.26**	−.18**	−.01	−.07	.12**	.39**

5. IE: System failure	1.06	0.28	.41**	.37**	.34**	.12	1	.12**	.04	.06	.21**	−.05	.01	.05	−.06	.03
6. Technology overload (TO)	2.16	.84	.64**	.53**	.29**	.71**	.17*	1	.86**	.91**	.71**	−.01	−.02	−.30**	.21**	.60**
7. TO: Information overload	2.56	1.23	.42**	.27**	.09	.67**	.08	.86**	1	.77**	.37**	.01	.04	−.17**	.13**	.57**
8. TO: Communication overload	2.55	1.16	.56**	.42**	.19*	.75**	.11	.93**	.83**	1	.43**	−.07*	.01	−.23**	.26**	.58**

9. TO: System overload	1.61	0.74	.63**	.65**	.45**	.39**	.25**	.77**	.42**	.55**	1	.05	−.11**	−.34**	.12**	.33**
10. Age	38.55	10.98	−.15	−.08	−.10	−.17*	−.07	.00	.03	−.05	.03	1	.39**	−.21**	−.28**	.03
11. Objective technology expertise	131.16	102.10	.01	−.01	.02	.01	.02	−.00	.06	.03	−.10	.44**	1	.11**	−.13**	.08*
12. Subjective technology expertise	140.68	16.09	−.14	−.19*	−.10	−.06	.08	−.29**	−.16	−.24**	−.35**	−.14	.16	1	−.10**	−.36**

13. Professional isolation	2.36	0.82	.16	.14	.09	.16	−.06	.27**	.17*	.31**	.19*	−.24**	−.11	−.12	1	.26**
14. ICT strain	8.99	3.80	.37**	.28**	.08	.49**	.11	.70**	.70**	.69**	.44**	.00	.07	−.32**	.28**	1

Note. M and SD are used to represent mean and standard deviation, respectively; variables 1 through 9 are within-person variables (Level 1); variables 10 through 14 are between-person variables (Level 2). Between-person correlations are shown below the diagonal; within-person correlations are shown above the diagonal with within-individual variables aggregated to the between-person level; Level 1 sample size, n = 856; Level 2 sample size, N = 143. ICT = information and communication technologies; IE = ICT events; TO = technology overload.
*$p < .05$. ** $p < .01$

One-Time Measures

The first one-time questionnaire assessed demographic variables, individual differences, and job characteristics at the beginning of the 2-week study. The three core variables, STE, OTE, and professional isolation, were included in this questionnaire. The second one-time questionnaire assessed various individual characteristics at the end of the study period. The measure of ICT strain was included in this questionnaire.

Subjective Technology Expertise (STE)

An adapted version of the computer self-efficacy questionnaire (Cassidy & Eachus, 2002; Spannagel et al., 2008) was used to measure the STE of every knowledge worker in the first questionnaire. Participants evaluated 29 statements (e.g., “I find working with digital systems very easy.,” “Digital systems help me to save a lot of time.”) on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The items were adapted to assess STE instead of computer self-efficacy. Moreover, one item that referred to outdated software (DOS-based packages) was removed. Cronbach’s α of the scale was .93.

Objective Technology Expertise

An adapted version of the computer expertise scale by Arning & Ziefle, 2007, 2009) was used to measure OTE. The items were adapted to fit the context of ICT use rather than general computer use. The first question ("For how long you have been working with the ICTs you described?") had to be answered with an even number in the range of 1–30. Following, the frequency of ICT usage ("How often do you use/work with these ICTs?") was assessed with a 4-point Likert scale ranging from 1 (*less than 1x per week*) to 4 (*daily*). As the last aspect, the ease of use ("Using ICTs is … for me.") was measured on a 4-point Likert scale ranging from 1 (*very easy*) to 4 (*very difficult*). Following the approach by 2009, the values for the last question were inverted before the overall objective technology expertise score was calculated by a multiplicative aggregation of the three individual scores.

Professional Isolation

To assess the degree to which participants experience professional isolation, we used the scale developed by Golden et al., 2008. Participants rated statements (e.g., "I miss face-to-face contact with coworkers") on a 5-point Likert scale ranging from 1 = *rarely* to 5 = *most of the time*. Cronbach's α was .81.

ICT-Related Strain was assessed using a version proposed by Ayyagari et al. (2011, who modified the original scale by Moore and Benbasat (1991). Participants indicated how often they experienced different situations (e.g., "I feel drained from activities that require me to use ICTs."). Answers were given on a 6-point Likert scale ranging from 1 = *never* to 6 = *daily*.

Daily Measures

The two daily questionnaires were divided into one morning and one evening questionnaire. The present study only focuses on the effects of ICT events and technology overload, which were included in the evening questionnaire.

Information and Communication Technologies Events

Previous research on ICT events (Braukmann et al. (2018)), ICT demands (Day et al. (2010, Day et al., 2012), and technostress (Ayyagari et al. (2011) was compared to identify relevant negative ICT events that relate to the system's characteristics. Four ICT-event items relating to technical problems, disruptions, and multichannel use were adopted from the negative ICT events derived by Braukmann et al. (2018). Events focusing on nontechnical aspects, such as communication overload, were excluded. Furthermore, from the ICT demands scale by Day et al., 2012, we included the "ICT hassles" subscale (5 items). Additionally, an adapted version of the system reliability scale used by Ayyagari et al. (2011; based on DeLone & McLean, 1992, 2003; Jiang et al., 2002) was included (3 items). As the aim of the scale was to measure events and not to include a person's perception, the items were adapted to measure reliable system functioning rather than the user's perception of its reliability. Moreover, as a result of the pretest, one item that assessed if technical problems of colleagues influenced one's own work, was added. The final 13 items were adapted to measure ICT events on a daily basis. Participants were asked to indicate which events occurred during their workday. They used a 6-point Likert scale ranging from 1 (*never*) to 6 (*almost all day*) to indicate how often they encountered the events during their day (e.g., "Today, I was disrupted during meetings by ICTs.," "I experienced software glitches."). Reliability of the scale was indicated with Cronbach's α ranging from 0.64 to 0.85, with an average of 0.79. Furthermore, participants had the opportunity to add additional events they experienced. A factor analysis of all final items with varimax rotation revealed four factors, which can be labeled as "technical error" (5 items), "reliability" (3 items), "interruptions and multichannel use" (3 items), and "system failure" (2 items). The role of the subdimensions is subject to additional explorative analyses that are reported in detail in the Appendix.

Technology Overload

An adapted version of the technology overload scale, developed by Karr-Wisniewski & Lu, 2010, was used to measure technology overload and its 3 subscales, information, communication, and system feature overload. Participants answered 3 items related to information overload (e.g., "I was overwhelmed by the amount of information I had to process."), 4 items about communication overload (e.g., "The availability of electronic communication created more of an interruption than it has improved communications."), and 5 items concerning system feature overload (e.g., "I was often distracted by software features."). All answers were given on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The 12 items were adapted to measure technology overload on a day level. Reliability was indicated by Cronbach's α ranging from 0.90 to 0.95.

Results

For data preparation and pretests (i.e., identifying dropouts, analysis of variance [ANOVA] testing for potential differences in samples, merging data, descriptives), we used SPSS (Version 27). All multilevel analyses (i.e., hypothesis testing, exploratory analyses) were performed with R Studio (Version 4.1.1), using the package lme4 (Bates et al., 2012). Simple slope analyses were conducted using the web-based tool by Preacher et al. (2010–2021) and Rweb1.03 (Version 3.6.3). For the post hoc mediation analysis, the MBESS package (Kelley & Lai, 2010) was used.

Descriptive Statistics

Means, *SD*s, Cronbach's α, and bivariate correlations are reported in Table 1. Cronbach's α for ICT events, technology overload, OTE, and STE was acceptable, ranging between α = .62 and α = .94.

Hypothesis Testing

Predictor variables on the within-person level were person-mean centered (Enders & Tofighi, 2007; Ohly et al., 2010). Predictive variables on the between-person level were grand-mean centered at the average of the total sample.

Data were analyzed by multilevel regression modeling (Aguinis et al. (2013)). The measurement provides a data structure with responses at different levels and times. Within-person level (day level 1/L1) responses were nested within individuals at the between-person level (person level/L2). In a first step, we computed a null model without any predictors to examine systematic variations at the between-person and within-person levels (comparing intraclass coefficients; Raudenbush & Bryk, 2002). *p* values were be obtained by likelihood ratio tests of the full model with the effect in question against the model without the effect in question. The single steps of the calculations were based on the recommendations of Aguinis et al. (2013). Model 1 included ICT events as a predictor of technology overload (Hypothesis 1). In Models 2 and 3, we added the level-2 predictors STE and OTE. By computing a random slope and a random intercept for each participant, individual variability in the dependent variables was accounted for Model 3. We built Model 4, including interaction terms to test moderating effects (i.e., to test whether variance in slopes across individuals can be explained by the level-2 predictors STE and OTE). In line with Hypothesis 1, we expect a significant positive relationship between negative ICT events and technology and workload (Model 1). In line with Hypotheses 2a and 2b, we expect a significant interaction effect of STE and OTE (Model 4). Against the background of the difficulty to detect cross-level interactions, especially in field studies due to limited statistical power (Mathieu et al., 2012; McClelland & Judd, 1993), we decided to report these interactions on an α level of 10% (cf. Jiang & Probst, 2016; Scherer et al., 2020).

Hypothesis 1 assumed that negative daily ICT events are positively related to daily technology overload. This assumption was confirmed ($t = 8.46$, $p < .001$).

Direct and Moderating Effect of Expertise

Hypothesis 2a assumed that person-level subjective technology expertise (STE) would moderate the relationship between day-level negative ICT events and technology overload. Results from multilevel regression revealed a significant direct negative effect of STE on technology overload ($t = -3.91$, $p < .001$) but did not confirm the hypothesized cross-level interaction (see Table 2). Thus, Hypothesis 2a was not supported.

Table 2

Results of Cross-Level Interactions Between Day-Level ICT Events, Subjective and Objective Technology Expertise, and Day-Level Technology Overload

Variable	Null model			Model 1			Model 2			Model 3			Model 4		
				Random intercept fixed slope (main effects)			Random intercept fixed slope			Random intercept random slope			Interactions		
Level 1	Est.	*SE*	*t*	Est.	*SE*	*t*	Est.	*SE*	*t*	Est.	*SE*	*t*	Est.	*SE*	*t*
Intercept	2.19	.06	34.82***	2.19	.06	34.84***	2.42	.03	9.89***	2.42	.02	9.91***	2.42	.02	9.93***
Frequency of day-level ICT events (ICT)				.33	.04	8.49***	.33	.04	8.48***	.31	.05	5.96***	.28	.05	6.08***
Level 2: Predictor variables															

Subjective technology expertise (STE)							−.02	.00	−3.91***	−.02	.00	−3.84***	−.02	.00	−3.91***
Objective technology expertise (OTE)							.00	.00	0.98	.00	.00	.84	.00	.00	1.01
Age (control variable)							−.01	.01	−0.95	−.00	.01	−.95	−.00	.01	−0.96
Cross-level interactions															
ICT × STE													−.00	.00	−1.21

ICT × OTE													.00	.00	3.09**
Variance components															
Within-person (L1) variance			.193			.175			.176			.163			.165
Intercept (L2) variance			.523			.527			.470			.474			.474
Slope (L2) variance												.088			.040
Additional information															
ICC			0.730												

−2 * log likelihood (FIML)			1,410.3			1,341.7			1,327.2			1,315.1			1,307.1
Pseudo R^2						.0953			.1146			.1303			.1406
Effect size f^2						.1054			.1294			.1498			.1637
Number of est. parameters			3			4			7			9			11
Δ Deviance (vs. Model 1)									68.6***			14.5***			14.5**

Δ Deviance (vs. Model 2)									14.5**			12.1**			12.1**
Δ Deviance (vs. Model 3)															8.1*

Note. For direct effects and cross-level interactions, two-sided testing was applied; ICT = frequency of day-level ICT events; STE = subjective technology expertise; OTE = objective technology expertise; ICC = intra class coefficient; L1 = Level 1; L2 = Level 2; Est. = estimate; SE = standard error; L1 daily surveys, n = 856, L2 sample size, N = 143; FIML = full information maximum likelihood; pseudo R2 is calculated with the Nagelkerke formula; effect size is based on pseudo R2 with f2 = R2/(1 − R2). * $p < .05$. ** $p < .01$. *** $p < .001$.

Hypothesis 2b assumed that person-level OTE would moderate the relationship between day-level negative ICT events and technology overload. Specifically, the positive relationship was expected to be weaker for individuals high in OTE than for individuals low in OTE. Multilevel results did not reveal a significant direct effect of OTE on technology overload but a significant cross-level interaction effect for OTE (t = 3.09 p = .004). The interaction plot is shown in Figure 2. Results of simple slope analysis indicated that both slopes ascend significantly (+1 *SD*, z = .42, p < .001; −1 *SD*, z = .14, p < .015). Results show that the positive relationship between ICT events and technology overload is stronger for individuals with a high level of OTE compared to a low level of OTE. Further, these positive relationships are not weakened by a high level of OTE. Thus, Hypothesis 2b was not supported.

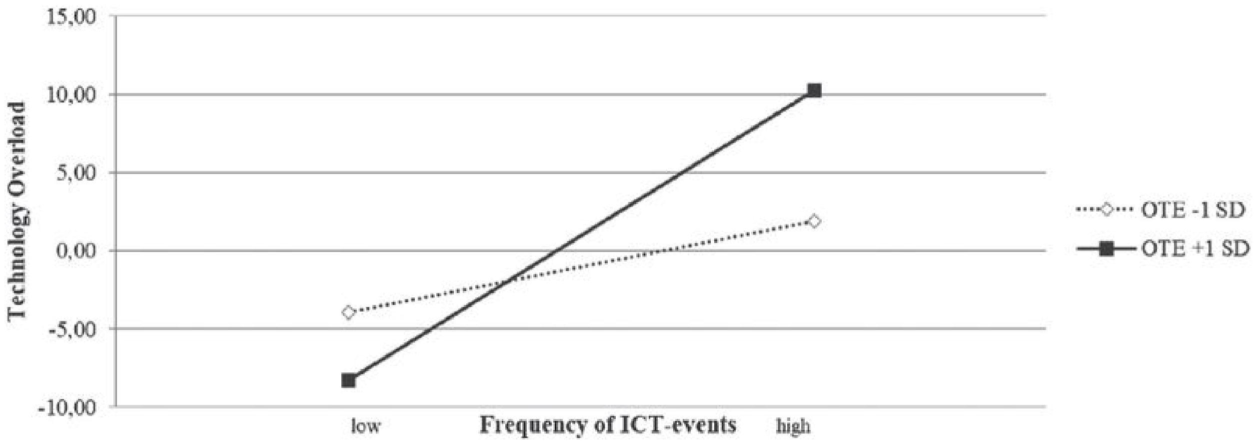

Figure 2

Plot of Significant Cross-Level Interaction (Hypothesis 2b) Illustrating the Moderation Effect of Objective Technology Expertise on the Relationship Between the Frequency of Daily Negative ICT Events and Daily Technology Overload

Note. Low = −1 standard deviation below mean; High = +1 standard deviation above mean; ICT = information and communication technologies; OTE = objective technology expertise.

Professional Isolation During Intense Telework

We conducted an exploratory analysis to study how technology overload and professional isolation impact ICT-related strain in knowledge workers during intensive telework. Results are shown in Table 3, indicating a significant direct effects of technology overload (t = 9.93, p < .001) and no effect of professional isolation (t = 1.42, p = .16) on ICT strain.

Table 3

Results of Exploratory Analyses on the Effect of Technology Overload and Professional Isolation on ICT-Related Strain

Variable	Model 1			
	Est.	*SE*	*t*	*p*
Intercept	0.41	1.38	0.30	.768
Technology overload[a]	3.40	.34	9.93***	<.001
Professional isolation	0.48	.34	1.42	.160

Age (control variable)	.00	.02	0.18	.856
Pseudo R^2	0.51			
Effect size f^2	1.03			

Note. Two-sided testing was applied; Est. = estimate; SE = standard error; sample size (Level 2) N = 120; pseudo R^2 is calculated with the Nagelkerke formula; effect size is based on pseudo R with $f^2 = R^2/(1 - R^2)$. [a] Technology overload is aggregated from Level 1 to Level 2; further explorative analyses with subdimensions are found in the Appendix. *** $p < .001$.

Additional Exploratory Analyses (Post Hoc)

To better understand unexpected results, we conducted additional post hoc analyses.[7]

First, an exploratory analysis of the ICT-event subscales identified in the factor analysis showed that reported technology overload varies across ICT events (see Table A1 in the Appendix). "Interruptions and multichannel use" revealed by far the largest effect on technology overload ($t = 8.45$, $p < .001$) in comparison to the other ICT subdimensions (technical errors: $t = 2.85$, $p = .004$; effects of reliability and system failure were not significant). In addition, we extended this analysis concerning variations in the experience of technology overload, taking the three dimensions of information, communication, and system overload into account. Results of the three tested models showed that the effects of the four ICT event types varied depending on the overload dimension (see Table A1). Results indicated significant direct effects of two ICT-event subscales on system overload ("technical error" $t = 4.46$, $p < .001$; "reliability" $t = 2.75$, $p < .001$), as well as significant effects of "interruptions" on information overload ($t = 7.41$, $p < .001$) and communication overload ($t = 9.16$, $p < .001$).

Second, we tested a more specified model, including the ICT-event and technology overload subscales, to investigate the role of STE and OTE (see Table A2 in the Appendix), as well as the hypothesized cross-level interactions. STE was not found to moderate any direct effect between ICT-event type and technology overload. A moderation effect of OTE was found for the ICT event "reliability" ($t = 1.93$, $p = .06$), which only reaches significance when one-sided testing is applied. The interaction plot is shown in Figure A1 in the Appendix.

Third, due to the differences between technology overload dimensions, we further analyzed the preregistered exploratory question considering the technology overload subscales (see Table A3). The analysis revealed that only the information overload subscale had a significant effect on ICT strain (t = 3.40, p < .001).

Against the background of unexpected results in the moderation analysis, we further investigated the mechanisms of ICT strain emergence, leaving individual differences in expertise aside. In a mediation analysis, we investigated the relationship between ICT events, technology overload, and strain (see Table A4). Results showed a significant indirect effect (z = 6.25, p < .001) with an effect size (k^2 = .44; Preacher & Kelley, 2011), indicating that the positive relationship between ICT events and ICT strain was fully mediated by technology overload.

Discussion

The present study aimed to highlight the relationship between daily ICT events and technology overload during times of intensive telework due to COVID-19-related measures. Specifically, we differentiated the moderating effect of subjective and objective technology expertise on this relationship. Furthermore, in an exploratory analysis, we addressed the role of professional isolation and technology overload on ICT-related strain. In additional exploratory analyses, we tested a mediation model and investigated the interplay of different ICT events, dimensions of technology overload, and expertise.

In the 2-week diary study, participants reported experiencing technical errors, issues relating to reliability, and interruptions daily. In line with our hypothesis, we found daily ICT events to be a significant predictor of technology overload, confirming Hypothesis 1. Additional analysis of the four ICT-event dimensions revealed that interruptions were the strongest predictor of technology overload. Furthermore, technical errors predicted technology overload, whereas reliability and system failure were not significant predictors. The results indicate that interruptions of work processes, for example, caused by multichannel use, technical features such as notifications, and availability-related issues (e.g., being interrupted by unplanned calls), mainly contribute to daily technology overload. These results are in line with research on information overload that highlights task interruptions and multitasking as central antecedents of information overload (Jackson & Farzaneh, 2012; Kirsh, 2000; Speier et al., 1999). Similarly, our study results portray that interruptions play a significant role in developing technology overload, confirming these prior assumptions. Earlier works on technology overload have suggested that reducing unnecessary interruptions by implementing central measures, such as company policies on email communication, will be critical to mitigating technology overload in the future (Karr-Wisniewski & Lu, 2010). Additionally, frequent technical issues may also contribute to technology overload. Thus, as suggested by Day et al. (2010, Day et al., 2012), providing adequate technical support to employees is essential. However, it is to be noted that in our sample, participants reported low levels of daily ICT events and technology overload.

Next, we proposed that technology experience, both subjective (STE) and objective (OTE), moderate the relationship between ICT events and technology overload, and that individuals high in STE (Hypothesis 2a) and high in OTE (Hypothesis 2b) will experience lower technology overload when ICT events are high.

The results of this study did not confirm STE as a moderator of the proposed relationship. However, the analysis showed a direct effect of STE on technology overload. On the basis of prior literature, we assumed that STE serves as a resource when employees face negative ICT events, consequently lowering technology overload. Instead, results indicate that STE can directly contribute to technology overload, with high STE being beneficial for employees. Especially when working in highly digitalized work environments, for example, during phases of intensive telework, employees may benefit from high STE, as they are less likely to experience technology overload. Existing models of technology interaction, such as the technology acceptance model (Venkatesh & Bala, 2008), highlight the importance of self-efficacy for users' willingness to interact with technology, as it impacts users' evaluation of the system (e.g., perceived ease of use). Thus, one explanation may be that, contrary to current assumptions, ICT events are not entirely independent of one's technology expertise. A person's STE may evoke (a) attitudes that reduce negative perceptions when evaluating ICT events or (b) behavior that buffers the occurrence of ICT events in the first place. With respect to attitudes, this means that a person who has confidence in successfully handling ICTs might rate a specific situation as less negative than a person low in STE. For example, a person with high STE might evaluate the simultaneous use of communication tools as a welcome and solution-enabling feature instead of a disruption of their workflow (e.g., due to notifications). Furthermore, many STE scales (e.g., computer self-efficacy) include items relating to solving technical errors (e.g., Cassidy & Eachus, 2002), which further supports this assumption. With respect to behavior, confidence in using ICTs might prevent the occurrence of certain ICT events in the first place. For instance, a user with higher STE may be more likely to switch off notifications not to become distracted. Further, individual differences, such as STE, may lead to differences in whether errors are attributed to the user or the system (e.g., Kim & Hinds, 2006). Prior research further highlights that individuals confident in using technical systems are more likely to try out new ICTs, knowing that errors might occur, as they have already developed strategies for solving such problems (O’Brien et al., 2012). These assumptions are further supported by recent studies suggesting that having confidence in using technological systems may decrease insecurities (Ulfert et al., 2022) and may thus protect employees from developing technology overload caused by ICT events. Consequently, it may be relevant to not only train employees in handling specific technologies but rather in developing the confidence in working with these systems. In our sample of knowledge workers, on average, participants reported high levels of STE. In line with our suggestions above, this could have further contributed to the low levels of reported daily ICT events and technology overload.

We further argued that OTE impacts how individuals evaluate a technology and related ICT events, making individuals high in OTE experience less technology overload due to ICT events. Hypothesis 2b was not confirmed. Although the interaction effect was significant, the interaction plot revealed that when ICT events were high, individuals high in OTE reported higher technology overload. In order to find possible explanations for these results, we take methodological and content-related aspects into consideration. First, technology overload as the day-level dependent variable was found to be quite low in our sample. This means that OTE might not have been a strain-buffering resource due to individuals not experiencing technology-related overload in the first place. This may have impacted the results of the analysis. Further, it is possible that the role of OTE differs depending on the subjective appraisal of the ICT event as being negative—rather than on the mere level of ICT-event frequency—and the level of technology overload. Second, the OTE measure used in this study used self-reports of lengths prior utilization of ICTs, frequency of use, and ease of using these systems. These aspects may be biased as employees may have difficulties accurately estimating their level of expertise. Additionally, at the time of the study (December 2020–February 2021), most participants have already gained a lot of experience interacting with ICTs. They may thus have relatively high OTE, which may have impacted their evaluations of ICT events. Nevertheless, the results may also point toward the fact that individuals high in OTE generally have a higher situation awareness and are more likely to detect error when interacting with technology (see, e.g., Endsley, 2018). Thus, individuals high in OTE may generally be more likely to detect ICT events (e.g., system functioning being slowed down) and experience technology overload as they react to these events (e.g., by checking for the cause). Individuals low in OTE may not even notice all ICT events that occur, leading to no consequences regarding their technology overload. Additional analyses support this interpretation further as the moderation effect was only found for "system reliability." This finding could indicate that individuals high in OTE are more likely to identify situations in which ICTs are not working consistently and react accordingly. Future research should investigate which processes evoke increased technology overload following ICT events and identify resources that buffer negative consequences for the employees.

An exploratory analysis highlighted the effects of technology overload and professional isolation on ICT-related strain. We assumed that due to mandated telework that was taking place at the time of the survey, employees would experience not only technology overload but also professional isolation due to decreased social interaction. Specifically, we assumed that professional isolation contributes to employees experiencing ICT-related strain. The analysis confirmed a strong direct effect of technology overload on ICT-related strain. Although these results did not confirm the significant effect of both technology overload and professional isolation, the correlational analysis revealed that both variables are related to ICT strain. As the constructs of technology overload and ICT strain are conceptually closely related, the stronger effect of technology overload may have suppressed the weaker effect of professional isolation. Thus, further analysis will be needed to understand better how professional isolation impacts strain. Further analysis of the technology overload subscales indicated that only information overload was significantly related to ICT strain, indicating that only specific dimensions of technology overload contribute to strain.

Lastly, a mediation analysis provided insights into the emergence of ICT strain. Technology overload was found to mediate the relationship between ICT events and ICT strain. In combination with the insights reported above, this supports the initial rationale of this registered report. ICT events do not fundamentally lead to strain but technology overload, as a consequence of the events, provokes strain.

Next to technology overload, additional work-related factors may play an important role. Prior works have highlighted the consequences of professional isolation for performance outcomes (Cooper & Kurland, 2002; Golden et al., 2008; Harrington & Santiago, 2006) but have thus far disregarded its role on strain. Professional isolation as a workplace characteristic—tightened during the pandemic—may still have healththreatening effects as employees feel more drained or tired from working remotely and communicating via ICTs (Zhang et al., 2021). Thus, to keep employees' ICT strain low, approaches will need to address both technology-related and job-related aspects.

Limitations and Future Research

Despite the promising results of this study, some critical remarks have to be made with regard to some of the measures and the sample used.

The study utilized a measure of OTE previously used in a variety of studies (Arning & Ziefle, 2007, 2009). However, thorough scale validation is still outstanding. Although the scale includes a self-rating of the length, frequency, and ease of using ICTs, which is a common approach to measuring technology skills (Peiffer et al., 2020), this may still be insufficient as a measure of objective technology experience. First, self-reports of expertise may be biased as individuals over- or underestimate their technology interaction and use (Peiffer et al., 2020). Second, the scale used in this study included various items that may have misrepresented the concept of OTE. The measure includes aspects relating to (a) the length of use, which may be impacted by the employee's age or tenure within a specific job; (b) the frequency of use, which does not give an indication of how well an employee may use these ICTs; and (c) ease of use, which might be more of an indicator of competence believes (i.e., STE) or technology acceptance. Future studies should replicate our findings with regards to OTE, including additional measures of OTE. For instance, ratings by colleagues or managers could give an indication of how well employees interact with ICTs. Furthermore, performance-based assessments may provide a better impression of employees' skills (Claro et al., 2012). Lastly, OTE was measured on a very general level (i.e., overall experience with ICTs), whereas employees may have worked with a very specific set of ICTs in their daily work. Going forward, studies should investigate whether specific OTE has a more substantial impact on the relationship of ICT events on technology overload and whether specific skill sets need to be differentiated. For instance, current digital competence frameworks differentiate between competence areas related to various ICT tasks, such as content creation or problem-solving (Carretero et al., 2017). These different competence areas may have distinct effects on the development of technology overload and should thus be addressed in future studies.

Additionally, the sample of the study may have impacted the results. Overall, participants reported low levels of daily ICT events and technology overload while reporting high levels of STE. These results may have been impacted by the fact that at the time of data collection, which took place among knowledge workers, many of the participants had already been working with ICTs intensively for an extended period of time. In Germany, lockdowns and remote work started being implemented around April 2020. By the time the study took place, employees may have already improved their expertise in working with ICTs. During these times, employees had to successfully solve many new situations and challenges relating to ICT use (Wang et al., 2021). Such mastery experiences can positively contribute to developing self-efficacy, and thus confidence in using ICTs (Usher & Pajares, 2008). As previously suggested and as indicated by our results, high STE may lead to individuals generally experiencing less technology overload, further explaining the low levels of reported technology overload. Other aspects that may have impacted the results are organizational characteristics. Prior research indicates that employees' ICT strain may differ depending on an organization's available technical resources, such as high-quality technological equipment or technical support (Day et al., 2012). In the present study, we did not consider aspects relating to employees' tasks, roles, or organizational aspects, such as digitalization levels. Thus, with regards to generalization, our results are restricted. Future studies should consider additional organizational factors and how these impact technology overload. These factors may have tremendous effects on the occurrence of ICT events, technology overload, and potentially even professional isolation as organizations strongly differ in how well they adapt to remote work.

Practical Implications

Currently, work environments are undergoing significant changes, as hybrid work has become one of the most discussed work trends (De Smet et al., 2021). Despite having gained much experience in working entirely remotely, employees currently still experience major challenges relating to the use of ICTs, such as increased strain, professional isolation, or impaired collaboration (Wang et al., 2021). Our study suggests that specific ICT events, such as interruptions and technical errors, may cause technology overload. Literature indicates that providing employees with effective ICTs as well as technical support may decrease ICT events and thus, as a consequence, mitigate effects on technology overload. Furthermore, organizations may provide employees with training that improves technical skills and subjective technology expertise, as it strongly impacts technology overload. Additionally, as interruptions and multichannel use pose the biggest risks for developing technology overload, employers should consider measures which are implemented at an organizational level, such as rules regarding the use of email or instant messenger systems.

Additionally, professional isolation may contribute to ICT strain and should thus be considered when implementing remote or hybrid work schemes. For instance, the implementation of specific virtual formats may foster social exchange and informal communication between colleagues. Ideally, such interaction formats should prevent professional isolation and stimulate social support beyond the predetermined ways of collaboration.

Conclusion

As the COVID-19 pandemic is ongoing, the continuous necessity to work virtually will have a tremendous impact on the world of work. Insights into factors impacting effective and healthy work environments gained during the pandemic will shape the future of work and our use of ICTs, even after employees return to offices. Our study particularly highlighted the impact of daily ICT events on technology overload and the role that subjective and objective technology expertise may play in supporting employees. Although our assumptions with regard to the moderating role of expertise were not fully supported, new insights were gained. STE may generally benefit employees, as it may decrease technology overload. With regards to OTE, further exploration will be required to identify whether individuals high in OTE typically identify more ICT events and whether they react differently to these events, potentially causing higher technology overload. Additional analyses further revealed that technology overload mediates the relationship between ICT events and ICT strain. Regarding ICT strain, it may be the case that not only technological aspects play a role but also job-related aspects, such as professional isolation. Moving forward, for employees to effectively work in virtual or hybrid work environments and support well-being, organizations will need to provide various support. This includes support before new technologies are implemented, continuous technical support and training, especially while employees work remotely, as well as support for keeping professional connectedness high.

Appendix

Table A1

Results Day-Level Effects Between ICT Events and Overload

	Model 1	Model 2	Model 3	Model 4
	DV: Technical overload	DV: TO—Information	DV: TO—Communication	DV: TO—System

Variable	Est.	*SE*	*t*	Est.	*SE*	*t*	Est.	*SE*	*t*	Est.	*SE*	*t*
Level 1												
Intercept	2.20	.06	34.76***	2.56	.09	28.97***	2.57	.09	30.34***	1.67	.06	29.95***
ICT technical error	0.10	.04	2.85**	−0.01	.06	−0.13	.08	.06	1.57	0.18	.04	4.46***
ICT reliability	0.01	.02	0.47	−0.02	.03	−0.61	−.03	.03	−1.16	0.06	.02	2.75**
ICT interruptions & multichannel	0.22	.03	8.45**	0.33	.04	7.41***	.34	.04	9.16***	0.05	.03	1.74
ICT system failure	0.12	.07	1.62	0.04	.12	0.33	.00	.10	0.02	0.25	.08	3.11
Variance components												
Within-person (L1) variance			.164			.486			.343			.216

Intercept (L2) variance			.532			.932			.944			.397
Additional information												
ICC (null model of DV)			0.730			0.636			.7014			.6125
−2 * log likelihood (FIML)			1,294.0			2,155.6			1,904.7			1,457.0
Pseudo R^2			.1573			.0730			.1246			.1091
Effect size f^2			.1867			.0788			.1423			.1225
Number of est. parameters			7			7			7			7

Note. For direct effects, two-sided testing was applied. DV = dependent variable; TO = Technical overload; Est. = estimate; ICC = intra class coefficient; ICT = frequency of day-level ICT events; L1 = Level 1; L2 = Level 2; Est. = estimate; SE = standard error; L1 daily surveys, n = 856, L2 sample size, N = 143; FIML = full information maximum likelihood; pseudo R^2 is calculated with the Nagelkerke formula; effect size is based on pseudo R^2 with f^2 = R2 /(1 − R^2).
** $p < .01$. *** $p < .001$.

Table A2

Results of Cross-Level Interactions Between Day-Level ICT Event Dimensions, Subjective and Objective Technology Expertise, and Day-Level Technology Overload

Variable	Null model			Model 1			Model 2			Model 3			Model 4		
				Random intercept fixed slope (main effects)			Random intercept fixed slope			Random intercept random slope			Interactions		
	Est.	*SE*	*t*	Est.	*SE*	*t*	Est.	*SE*	*t*	Est.	*SE*	*t*	Est.	*SE*	*t*
Level 1															
Intercept	2.19	.06	34.82***	2.20	.06	34.76***	2.03	.53	3.85***	1.78	.51	3.45***	1.77	.52	3.43***
Frequency of day-level ICT events															
“Technical error (TE)”				.10	.04	2.85**	0.10	.04	2.85**	.09	.05	2.06*	.07	.05	1.59

"Reliability of the system (RL)"				.01	.02	0.47	0.01	.02	0.48	.01	.03	0.26	.01	.03	0.25
"Interruptions and multichannel use (IR)"				.22	.03	8.45***	0.22	.03	8.44***	.20	.03	6.53***	.19	.03	6.33***
"System Failure (SF)"				.12	.07	1.62	0.12	.07	1.63	.20	.09	2.23*	.22	.09	2.31*
Level 2: Predictor variables															

Subjective technology expertise (STE)							−.01	.00	−3.79***	−.02	.00	−4.03***	−.01	.00	−3.83***
Objective technology expertise (OTE)							−.00	.00	0.51	.00	.00	0.66	.00	.00	0.37
Age (control variable)							−.00	.13	0.32	.11	.13	0.82	.11	.13	0.83
Cross-level interactions															
ICT-TE × STE													−.00	.00	−0.58

ICT-RL × STE													−.00	.00	−0.39
ICT-IR × STE													−.00	.00	−0.03
ICT-SF × STE													.00	.00	0.78
ICT-TE × OTE													.00	.00	1.06
ICT-RL × OTE													.00	.00	$1.93^{+, a}$
ICT-IR × OTE													−.00	.00	−0.12
ICT-SF × OTE													−.00	.00	−0.27

Variance components															
Within-person (L1) variance			.193			.164			.164			.134			.134
Intercept (L2) variance			.523			.532			.478			.486			.486
Slope (L2) variance TE												.063			.058
Slope (L2) variance RL												.026			.021

Slope (L2) variance IR												.024			.021
Slope (L2) variance SF												.179			.168
Additional information															
ICC			0.730												
−2 * log likelihood (FIML)			1,410.3			1,294.0			1,280.3			1,245.7			1,232.8
Pseudo R^2						.1573			.1745			.2167			.2318
Effect size f^2						.1867			.2113			.2767			.0319

Number of est. parameters			3			7			10			24			32
Δ Deviance (vs. Model 1)							13.67**			13.67**			13.67**		
Δ Deviance (vs. Model 2)										34.68**			34.68**		
Δ Deviance (vs. Model 3)													12.81		

Note. For direct effects and cross-level interactions, two-sided testing was applied. Est. = estimate; ICT = frequency of day-level ICT events; STE = subjective technology expertise; OTE = objective technology expertise; TE = technical error; IR = interruptions and multichannel use; RL = reliability of the system; SF = system failure; ICC = intra class coefficient; L1 = Level 1; L2 = Level 2; Est. = estimate; SE = standard error; L1 daily surveys, n = 856, L2 sample size, N = 143; FIML = full information maximum likelihood; pseudo R^2 is calculated with the Nagelkerke formula; effect size is based on pseudo R^2 with $f^2 = R^2/(1 - R^2)$.

[a] p = .06 (two-sided testing).

[+] $p < .10$. * $p < .05$. ** $p < .01$.

Table A3

Results of Exploratory Analyses on the Effect of Technology Overload Subdimensions and Professional Isolation on ICT-Related Strain

Variable	Model			
Intercept	.39	1.36	0.29	.774
Technology overload[a]				
Information overload	1.67	.49	3.40***	<.001
Communication overload	0.85	.52	1.63	.106
System overload	0.39	.45	0.86	.393
Professional isolation	0.55	.34	1.63	.106
Age (control variable)	.01	.02	0.39	.700
Pseudo R^2	.5372			
Effect size f^2	1.16			

Note. Two-sided testing was applied; Est. = estimate; ICT = information and communication technologies; SE = standard error; sample size (Level 2) N = 120; pseudo R2 is calculated with the Nagelkerke formula; effect size is based on pseudo R with f 2 = R2 /(1 − R2). a Technology overload subdimensions are aggregated from Level 1 to Level 2. *** p < .001.

Table A4

Results of Regression Analyses for Mediation of Technology Overload Between Frequency of ICT Events and ICT Strain

Model	Est.	*SE*	*t*	*p*	CI (lower)	CI (upper)	R^2	RSE	d*f*	*F*
Model 1 (DV: ICT strain)					.04	.26	.13	3.59	118	18.19 (1, 118)
Intercept	4.51	1.13	4.00***	<.001	2.28	6.74				
Frequency of ICT events[a]	2.73	.64	4.27***	<.001	1.45	4.00				
Model 2 (DV: Technology overload[a])					0.24	0.51	.38	.61	118	70.98 (1, 118)
Intercept	0.65	.19	3.39***	<.001	0.27	1.02				
Frequency of ICT events[a]	0.91	.11	8.43***	<.001	0.70	1.13				

Model 3 (DV: ICT strain)					0.36	0.62	.50	2.73	117	59.20 (2, 117)
Intercept	2.01	.90	2.24*	.022	0.23	3.79				
Frequency of ICT events[a]	−.79	.62	−1.28	.202	−2.01	0.43				
Technology overload[a]	3.87	.42	9.33***	<.001	3.05	4.69				
Mean bootstrapped indirect effect[b]	3.52			<.001	2.36	4.81				
Effect size κ^2 [c]	0.44									

Note. Two-sided testing was applied; DV = dependent variable; Est. = estimate; SE = standard error; RSE = residual standard error; R^2 = adjusted R squared; ICT = frequency of day-level ICT events. F = F statistic; sample size (Level 2) N = 120. [a] ICT events and technology overload are aggregated from Level 1 to Level 2. [b] z = 6.25, R = 0.7088, R^2 = 0.5024, F statistics = 59.0737 (2, 117). [c] κ^2 = the proportion of the maximum possible effect (Preacher & Kelley, 2011).
* $p < .05$. *** $p < .001$.

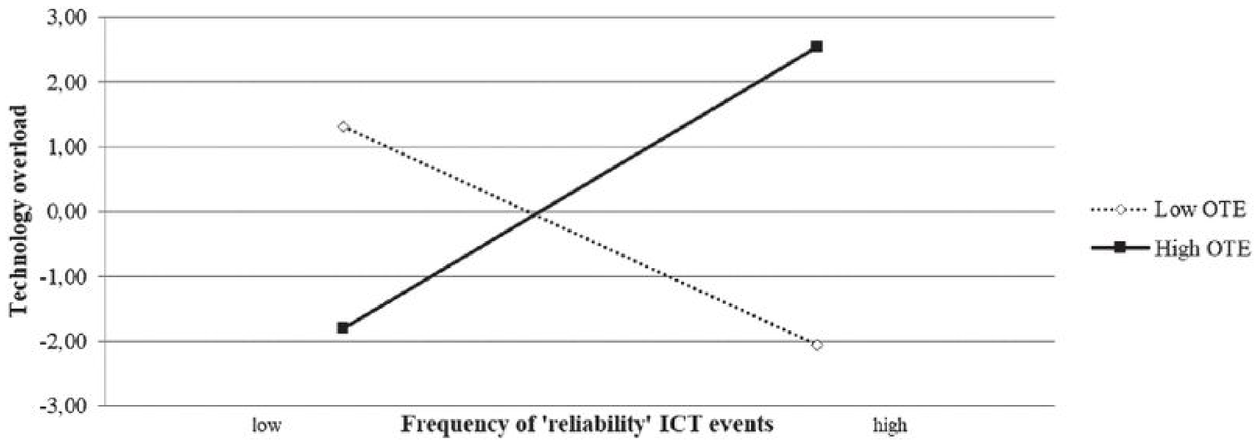

Figure A1
Plot of Significant Cross-Level Interaction in Post Hoc Analysis

Note. Low = −1 standard deviation below mean; high = +1 standard deviation above mean; OTE = objective technology expertise; ICT = frequency of day-level ICT events.

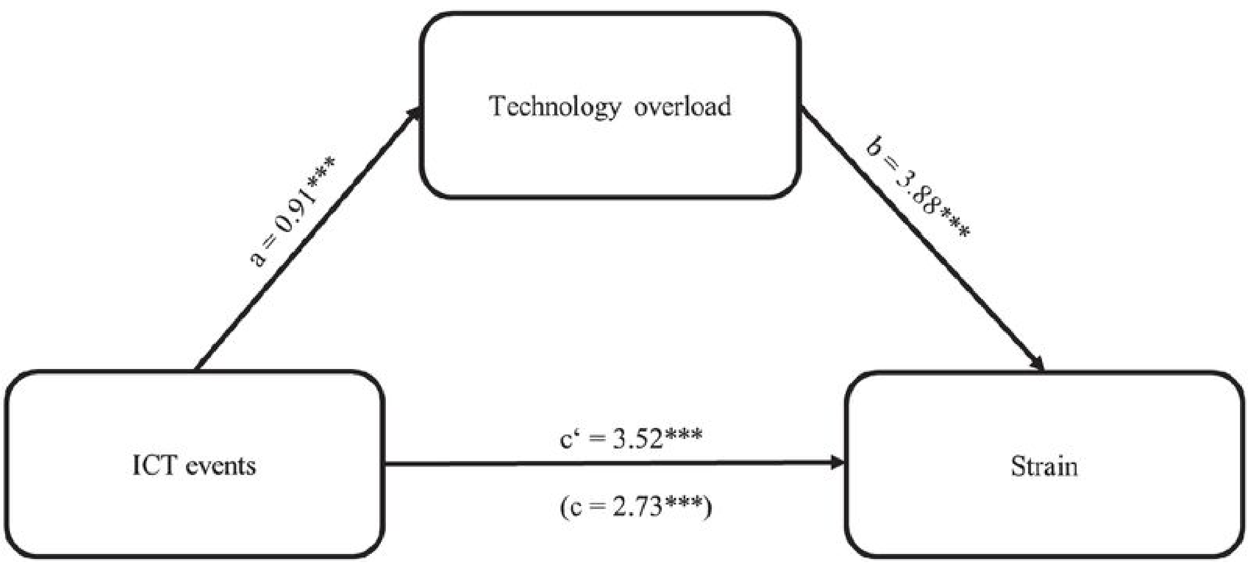

Figure A2
Mediation Model Tested in Post Hoc Analysis With Results

Note. ICT events = daily frequency of ICT events aggregated to the person level; technology overload = daily technology overload aggregated to the person level; strain = ICT-related strain assessed after the set of daily reports was finished; a, b, c = direct paths; c’ = indirect path; ICT = frequency of day-level ICT events.

*** $p < .001$.

Supplementary materials

pdf open-practice-disclosure_Scherer.pdf 359 KB

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Footnotes

1. The originally reviewed and in principle accepted registered report of this article can be found on OSF https://osf.io/gxnks/ ↩

2. The data and analytic code of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions. ↩

3. We specifically aimed to assess participants understanding of the instructions, explanations, as well as the daily ICT events and technology overload items. For this, participants had to describe in writing how they understand the different parts of the questionnaires (e.g., individual items). Further, we asked participants to indicate additional ICT events they consider important. ↩

4. This study followed the ethics recommendations by the German Psychological Society and was thus exempt from approval by the ethics committee. ↩

5. All experts were either bilingual or were professionally proficient in English and spoke German as their native language. ↩

6. This section only includes measures relevant to this article. For an overview of all measures and materials used in this study, please refer to https://osf.io/7ex58/ ↩

7. We would like to thank the reviewers and the editor for their constructive feedback and advice on our registered report and earlier versions of this paper as well as for their suggestions to add post-hoc analyses. ↩

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