Computers in Human Behavior 124 (2021) 106899

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

From cognitive overload to digital detox: Psychological implications of telework during the COVID-19 pandemic

Josephine B. Schmitt [a,*], Johannes Breuer [b], Tim Wulf [c]

[a] Center for Advanced Internet Studies (CAIS), Universitätsstraße 104, 44799 Bochum, Germany
[b] GESIS – Leibniz Institute for the Social Sciences, Unter Sachsenhausen 6-8, 50667, Cologne, Germany
[c] LMU Munich, Department of Media and Communication, Oettingenstraße 67, 80538, Munich, Germany

ARTICLE INFO

Keywords:
Digital detox
Cognitive overload
Telework
Well-being
Work performance

ABSTRACT

For most people, telework during the COVID-19 pandemic necessitates the increased use of digital tools. Although working from home can enhance flexibility, it comes with various psychological challenges, all of which can be substantially exacerbated for people during the COVID-19 pandemic. The increased need to use digital tools can create cognitive overload that may negatively impact work productivity and well-being. The idea of digital detox has received increasing attention in the last few years as a means for recovering from stress caused by the use of digital media. This paper presents an analysis of the relationships between the use of digital work tools, the feeling of cognitive overload, digital detox measures, perceived work performance, and well-being. Results from an online survey (N = 403) conducted during the period of strict lockdown measures in Germany in April and May 2020 indicate that the relationship between the use of text-based tools and well-being, but not perceived job performance, is mediated by cognitive overload. These relationships were not found for the use of videoconferencing tools. However, for users of these tools, the number of digital detox measures moderates the relationship between cognitive overload and the perception of work demands.

The COVID-19 pandemic disrupted people's lives in many regards. Work is one area severely affected. Due to social distancing measures and lockdowns, many must work from home, relying on videoconferencing (e.g., Zoom, Skype) or text-based work management and communication tools (e.g., Slack, Trello, e-mail) as substitutes for in-person interaction and information access. Although working from home can generally increase flexibility, it comes with various social and psychological challenges (e.g., Shepherd-Banigan, Bell, Basu, Booth-LaForce, & Harris, 2016). With the COVID-19 pandemic, many of these challenges are exacerbated because of the overall uncertainty of the situation, issues related to childcare and other duties, and the lack of physical social contact. People are likely to experience more stress and overload because of the sudden and unexpected increased use of digital tools to manage workflow. The increased need to use digital tools may introduce changes in working routines or expectations of needing to work longer and faster (Karr-Wisniewski & Lu, 2010). These feelings of being stressed and overloaded by organizing work primarily through digital technologies may, in turn, negatively impact productivity and well-being (Eppler & Mengis, 2004).

Irrespective of the changes brought about by the COVID-19 pandemic, in response to the societal phenomenon of being "permanently online, permanently connected" (Vorderer et al., 2017), concepts like *digital minimalism* and *digital detox* have received increasing attention recently. The general idea is to take a break from online and digital media, deliberately engaging in "non-digital" tasks in order to avoid or recover from digital stress and overload, and focus on the physical world (Newport, 2019; Syvertsen & Enli, 2019).

This paper presents an analysis of the relationships between the use of digital work tools, the feeling of cognitive overload, digital detox measures, work performance and well-being using an online survey conducted during the COVID-19 pandemic's period of strict social distancing and lockdown measures in Germany in April and May 2020.

1. Cognitive overload, well-being, and work performance

Although digital media can facilitate social life, learning, and work in many ways, they also may cause feelings of being overloaded. From a psychological perspective, this perception can generally be defined as a state in which the informational input exceeds cognitive capacities (Eppler & Mengis, 2004). In psychological and social-scientific research,

* Corresponding author. Center for Advanced Internet Studies (CAIS), Universitätsstraße 104, 44799 Bochum, Germany.
E-mail addresses: josephine.schmitt@cais.nrw (J.B. Schmitt), johannes.breuer@gesis.org (J. Breuer), tim.wulf@ifkw.lmu.de (T. Wulf).

https://doi.org/10.1016/j.chb.2021.106899
Received 10 August 2020; Received in revised form 26 May 2021; Accepted 4 June 2021
Available online 9 June 2021
0747-5632/

there are various terminologies that address this phenomenon: Regarding interactive learning systems researchers commonly refer to *cognitive overload* or *cognitive load* (e.g., Jiang, Kalyuga, & Sweller, 2020; Sweller, 1994; van Gog, Paas, & Sweller, 2010), meaning that "learners may be overwhelmed by the number of interactive information elements that need to be processed simultaneously before meaningful learning can commence" (van Gog et al., 2010, p. 375). Similarly, researchers dealing with cognitive challenges of learning in hypertext environments often use the term *cognitive overhead* (or "lost-in-hyperspace"-phenomenon), addressing the limitation of the human working memory for information processing while browsing texts with hyperlinks (e.g., Zumbach, 2006; Zumbach & Mohraz, 2008). Some authors also use the term *information overload* to describe the psychological consequences of being confronted with a large and heterogeneous set of online news sources (e.g., Schmitt, Debbelt, & Schneider, 2017), or being overwhelmed by functions and content on e-learning platforms (e.g., Chen, Pedersen, & Murphy, 2011). Others—mainly referring to an overwhelming usage of social media—talk about *communication overload* or *social overload* (e.g., Choi & Lim, 2016; Lee, Son, & Kim, 2016). Finally, concerning the organisational, work-related use of digital information and communication technologies, various authors also use the term *techno(-logy) overload* (e.g., Karr-Wisniewski & Lu, 2010; Tarafdar, Qiang, & Ragu-Nathan; 2010). To avoid confusion due to heterogeneity in the terminology, in this article the term cognitive overload is used as shorthand for various forms of overload ascribed to the overuse of digital tools.

The predictors for cognitive overload are diverse and often intertwined. There are various individual variables (e.g., cognitions, attitudes, frustration levels, technical skills, self-efficacy), situational factors (e.g., task difficulty, time constraints, technical support), and media-related aspects (e.g., technological, and social demands of the media used, quality and quantity of information) affecting cognitive overload (e.g., Chen et al., 2011; Eppler & Mengis, 2004; Schmitt et al., 2017; Tarafdar, Tu, & Ragu-Nathan, 2010; Zumbach & Mohraz, 2008).

Due to the COVID-19 pandemic, about 50 percent of the employees in Germany had to work from home in March 2020 (Bitkom, 2020)—initially for an unspecified, indefinite time. Although telework also may have enabled flexibility, autonomy, and creativity, many employees perceived it to be more demanding and stressful than working in the office (Haufe, 2020). The reasons are manifold. About half of the employees reported that they have never worked from home before and, thus, were insufficiently equipped with the necessary hardware or software and the required knowledge and skills. Previous studies have shown that an increased use of mobile information and communication technologies in the workplace, in general, can make the working environment more complicated (Bawden & Robinson, 2009). Consequently, many employees immediately had to face possible doubts and insecurities in dealing with digital tools and acquire relevant technical skills to meet work requirements (De', Pandey, & Pal, 2020).

For most people – at least the ones working in office jobs – telephone and web conferences substituted for personal meetings with colleagues and customers during the lockdown (Bitkom, 2020), while managerial functions as well as organizational tasks are relocated into "always on" online spaces (e.g., text-based management and chat tools) (Haufe, 2020). Importantly, in such situations, the division between work and non-work is less bounded by clear temporal and physical markers (Carrigan & Duberley, 2013; Lüthje & Thiele, 2020). In addition, the increased need to use digital tools accompanied by a constant stream of information and communication may foster the impression that there is a need to work longer and faster (Eurofound and the International Labour Office, 2017), which can create feelings of overload.

Feeling overloaded by the use of digital tools may result in ineffective information processing, confusion, loss of control, psychological stress (Eppler & Mengis, 2004)—or even an increase of depressive symptoms (Matthes, Karsay, Schmuck, & Stevic, 2020; Reinecke et al., 2017). The latter may have even more severe consequences with the individual, social, and societal demands of the COVID-19 pandemic being especially challenging to mental health. Notably, cognitive overload may also lead to rejection or avoidance of using such products and tools (Lee et al., 2016). Studies have also shown that overload due to an overwhelming digital communication environment negatively influences job productivity (e.g., Karr-Wisniewski & Lu, 2010) and job satisfaction (e.g., Tarafdar et al., 2010). Considering the ubiquity and necessity of digital tools during the height of the COVID-19 pandemic, there is reason to assume that the resulting cognitive overload is one contributing factor to a reduction in employees' productivity and well-being.

2. "Digital detox" as a strategy for handling cognitive overload

It is not always possible for individuals to eliminate the conditions leading to cognitive overload, but people can adopt strategies to handle overload and its negative consequences. Constant stress and reduced work productivity can have severe consequences in the long run, for both employees (psychologically) and for organizations (economically) (e.g., De Jonge, Spoor, Sonnentag, Dormann, & van den Tooren, 2012). To deal with cognitive overload and its potential consequences, concepts such as *digital minimalism* and *digital detox* have received increasing attention recently—however, primarily as buzzwords in popular-science blogs, self-help books, lifestyle websites and social media (Syvertsen & Enli, 2019). They purvey a certain minimalist "philosophy of technology use" (Newport, 2019, p. 28). The general idea behind these concepts is taking a conscious break from digital media by engaging in explicitly "non-digital" tasks focusing on the physical world (Syvertsen & Enli, 2019).

Different lines of research point to positive effects of such strategies: For instance, self-control enhancement, switching off notifications, and powering off electronic devices at a certain time in the evening, seem to improve sleep quality and quantity and, thus, increase work productivity the following day (Lanaj, Johnson, & Barnes, 2014). The use of digital detox apps (i.e., apps supporting users to monitor and limit their smartphone time) can also prevent potential harmful effects of social networking sites on well-being among young people (Schmuck, 2020). Other studies have found that answering emails only at a predefined time during a day may reduce stress while working (Kushlev & Dunn, 2015). Taken together, these findings indicate that digital detox strategies may have an overall positive impact on feelings of well-being.

3. Hypotheses

Based on the previous findings and considerations outlined above, this study was designed to test the following hypotheses:

Hypothesis 1: The increased use of digital work tools is positively related to feelings of cognitive overload.

Hypothesis 2: Perceived cognitive overload is negatively related to

a) perceived work performance.

b) feelings of well-being.

Hypothesis 3: Cognitive overload plays a mediating role in the relationship between the use of digital tools and

a) perceived work performance.

b) well-being.

Hypothesis 4: The relationships between perceived cognitive overload and

a) feelings of well-being are moderated by "digital detox" measures.

b) perceived work performance is moderated by "digital detox" measures.

Fig. 1 gives an overview of the hypothesized relationships for this study.

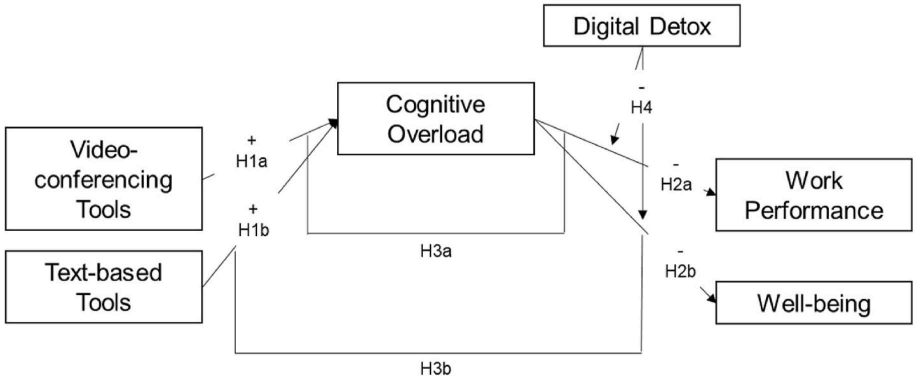

Fig. 1. Overview of the hypothesized relationships.

4. Methods

4.1. Sample

The data used in this analysis originates from a more comprehensive online survey[1] created with SocSci Survey[2] conducted from 27th April 2020 to 07th May 2020 in Germany. The sample was drawn from a German non-probability online access panel (Leiner, 2016). The study was additionally advertised via the authors' private accounts on Facebook and Twitter. In total, 615 people took part in the online survey. Participants who completed the questionnaire in less than five min (n = 66) and whose data are incomplete regarding the variables of interest (n = 208) were excluded from the analyses. As the focus was on consequences of an *increased* need for using digital tools for work during the pandemic, the survey included a filter, so that only those who reported to use these tools *at least as often as before the pandemic* received the questions on cognitive overload, perceived work performance, and digital detox. Accordingly, respondents who indicated that they do not use videoconferencing or text-based tools at all or that they use them less frequently than before the pandemic were not included.[3] Thus, the final sample consisted of $N = 403$ respondents, age 18–87 years (M_{age} = 38.93, SD_{age} = 17.49; n_{female} = 259, n_{male} = 141, $n_{non\text{-}binary}$ = 3). Ninety-four respondents reported at least one child living in their household. The hypotheses and analysis plan for this study have been pre-registered with AsPredicted.[4]

4.2. Measures

4.2.1. Use of digital work tools

Participants were asked whether their use of a) videoconferencing tools (e.g., Zoom, Skype) and b) text-based management and chat tools (e.g., Slack, Trello) differed compared to before the COVID-19 pandemic. Ratings ranged from 1 (*significantly more seldom*) to 7 (*significantly more often*). Participants could also indicate that they never used these tools before (see Table 1).[5]

Table 1
Use of digital work tools.

	n	M (SD)	Min	Max
Videoconferencing tools	395 (8 non-users)	4.463 (0.68)	2	5
Text-based tools	258 (147 non-users)	3.849 (0.931)	1	5

4.2.2. Cognitive overload

Perceived cognitive overload was assessed with the adapted technology overload scale used by Choi and Lim (2016). Sample items include: "By using digital work tools, I am forced to do more work than I can handle.", "By using digital work tools, I am forced to work with very tight time schedules.". Participants indicated their answers on a 7-point Likert-scale (1 = *strongly disagree*, 7 = *absolutely agree*). A mean score was computed for further analyses (M = 2.71, SD = 1.60, min = 1, max = 7, Cronbach's α = .83).

4.2.3. Perceived work performance

In order to measure perceived work performance, two items were adapted from Karr-Wisniewski and Lu (2010) to assess technology-based work performance: a) "Overall, I feel that this technology has *efficiently* enhanced my job productivity." b) "Overall, I feel that this technology has *effectively* enhanced my job productivity." Participants indicated their answers on a 7-point Likert-scale (1 = *strongly disagree*, 7 = *absolutely agree*). The mean score of these two items was used for further analysis (M = 3.13, SD = 1.81, min = 1, max = 7, Spearman-Brown coefficient = 0. 79[6]).

4.2.4. Digital detox

Digital detox strategies were measured via an open-ended question. The answers were coded into categories (e.g., outdoor activities/sports, defining media-free time periods, temporarily leaving the mobile phone unattended). A sum score was calculated over the number of different detox measures each person reported to engage in (M = 0.94, SD = 1.17, min = 0, max = 5). Table 2 gives an overview over the full list of categories and counts as well as example quotes.

[1] The survey also included several scales and questions on media-induced nostalgia, worries, and loneliness which are not reported here.

[2] https://www.soscisurvey.de.

[3] To quantify how many respondents were excluded based on this filter in the questionnaire: n = 119 people reported that they do not use videoconference tools and n = 274 respondents indicated that they do not use work management and communication tools at all. By comparison, only n = 7 participants used videoconference tools less frequently than before the pandemic, and n = 6 users of text-based tools reported to use them less frequently.

[4] See https://aspredicted.org/df4qr.pdf for the preregistration document.

[5] With the exception of the questions on well-being, only those participants who said that they used one of the mentioned digital work tools *at least as often as before* the COVID-19 pandemic (= min. 3 on the scale) were asked to answer the following questions.

[6] We report the Spearman-Brown coefficient instead of Cronbach's alpha here as this is the recommended measure of reliability for two-item scales (Eisinga, Grotenhuis, & Pelzer, 2013).

Table 2
Overview of digital detox measures, counts, and example quotes.

Digital Detox Measures	Count	Example Quote
Leaving the smartphone unattended	105	"When I go for a walk, I leave my smartphone at home"
Clearly defined intervals of media use	56	"Putting my smartphone into "sleep mode" between 8 pm and 7 am"
Outdoor activities/sports	51	"Doing Yoga"
Non-digital media	40	"Reading a book instead of using my smartphone"
Deinstalling/not using apps	12	"I do not use certain apps"
Deactivate notifications	11	"I deactivated notifications"
Housework/Cooking	8	"Cooking"
Not further specified non-digital tasks	8	"Distraction with non-digital tasks"
Switching off Wifi/mobile data	8	"Switching off Wifi at home to be unavailable"
Talking to people (on the phone)	6	"Talking directly to people"
Gardening	6	"I work in the Garden"
Playing board games	6	"Board game nights"
Avoiding/not using social media	6	"I don't use Facebook"
Being creative	5	"Writing"
Not using the computer	5	"Switching off the laptop"
Avoiding non-productive tasks	5	"I try to avoid non-productive tasks"
No smartphone	3	"I don't have a smartphone"
Meditation/Mindfullnes	3	"I track down what I 'really' need"
Ignoring links	1	"I do not open links people send me"
Nothing	58	
Sum	**403**	

4.2.5. *Well-being*

Well-being was measured with the "Perceived Stress Questionnaire (PSQ-20)" (Fliege, Rose, Arck, Levenstein, & Klapp, 2009). Sample items: "You feel that too many demands are being made on you.", "You are full of energy.". The PSQ-20 is a validated instrument consisting of four subscales: worries, tension, loss of joy, and demands. To increase consistency across scales, and differing from the original scale, participants in the present study indicated their answers on a 7-point Likert-scale (1 = *strongly disagree*, 7 = *absolutely agree*). Reversed items were recoded. Internal consistency coefficients of the subscales were high in terms of Cronbach's α (worries: .85, tension: .88, demands: .84, loss of joy: .82). Mean scores for all four subscales were used for further analyses (worries: $M = 3.54$, $SD = 1.61$, tension: $M = 3.73$, $SD = 1.70$, demands: $M = 3.38$, $SD = 1.69$, loss of joy: $M = 3.71$, $SD = 1.36$).

5. Results

The first section in this chapter (5.1) summarizes the results of two path models which were calculated to analyse the hypothesized relationships (H1 – H4; for an overview of the assumed relationships and hypotheses see Fig. 1). In a second subsection (5.2) additional findings regarding control variables, such as the number of children in the household and participants' age, are provided.

5.1. *Hypothesis tests*

Hypotheses were tested by calculating two path models with MLR estimation using the package *lavaan* (Rosseel, 2012) for R (R Core Team, 2020): one for videoconferencing tools (e.g., Zoom, Skype; Model 1) and one for text-based management and chat tools (e.g., Slack, Trello; Model 2). For both models, the predictor variables cognitive overload and digital detox were mean-centered prior to the analyses and tested for the significance of indirect effects with bootstrapped confidence intervals with 5000 samples. Only cases with complete data were included in the analyses (listwise deletion). Results were controlled for age and the presence of children in the household as parents could likely be particularly stressed due to the closing of schools or day-care centres.

For Model 1, the analysis revealed that the use of videoconferencing tools ($b = .100$, 95% CI [-0.123, 0.322], $\beta = .048$) was not positively related to perceptions of overload. By contrast, a higher usage of text-based tools ($b = .259$, 95% CI [0.067, 0.450], $\beta = .158$) was positively related to cognitive overload. Hence, hypothesis H1 was only supported for people who increased their use of text-based tools during the COVID-19 lockdown.

In both models, cognitive overload was significantly and positively related to all four well-being subscales (for all estimates see Table 3 and Table 4). The more people feel overloaded by using digital tools for work, the more they experience demands, loss of joy, tensions, and worries. This result supports hypothesis H2b. Further, there is a small positive but significant relationship between digital overload and perceived work performance in Model 1 (b = .174, 95% CI [0.059, 0.289], $\beta = .155$) contradicting hypothesis H2a—meaning that people who used videoconferencing tools at least as often as before the pandemic reported a higher perceived work performance when they experienced higher cognitive overload.

Moreover, there was a significant indirect relationship between using text-based tools and all four well-being subscales that was mediated by perceived cognitive overload (H3b). Higher use of text-based tools during the COVID-19 pandemic was significantly related to increased feelings of overloaded that in turn, were positively related to a higher perception of demands, loss of joy, tension, and worries (for an overview of all regression coefficients, see Tables 3 and 4).

Hypothesis 4 proposed that digital detoxing measures would moderate the relationship between perceived cognitive overload and a) work performance and b) well-being. The number of different digital detox measures moderated the relationship between perceived cognitive overload and the perception of demands only in Model 1 (videoconferencing tools). Fig. 2 shows that for users of videoconferencing tools reporting an increasing number of digital detox measures, the size of the relationship between digital overload on perceived demands decreases considerably.

5.2. *Additional findings*

The presence of children in the household was associated with higher feelings of cognitive overload and perceived demands, independent of the digital tools used. In Model 1, age was negatively related to the three scales demand, tension and worries. In Model 2, there were significant negative relationships between age, tension and worries (see Tables 3 and 4).

6. Discussion

The present study revealed several relationships between the use of digital work tools, cognitive overload, the use of digital detox measures, perceived work performance, and different dimensions of well-being. While some of those were the same for videoconferencing and text-based tools, others were only found for one tool type. People reporting an increased use of text-based tools in the context of telework also reported increased perceptions of feeling overloaded, while those reporting increased use of videoconferencing tools did not. One reason may be the difference between synchronous communication and asynchronous communication and their respective demands. With videoconferencing tools, employees communicate at a time slot that is often scheduled. Text-based tools, however, are asynchronous and may lead to the experience that while working on tasks, other tasks accumulate that cannot be addressed simultaneously or swiftly or that key communication (e.g., by email or chat) may be missed (Becker, Alzahabi, & Hopwood, 2013; Reinecke et al., 2017). This may be especially challenging for younger, less experienced people who may have difficulties in prioritizing tasks (Kushlev & Dunn, 2015; Nurmi, 2011). Another reason for the more challenging character of text-based tools could further be

Table 3
Coefficients and conditional indirect effects for Model 1: Videoconferencing tools (n = 395).

Regressions	β	*b*	*SE*	*p*	95% CI		R^2
					Lower Bound	Upper Bound	
Cognitive Overload							0.025
Videoconferencing Tools (X)	.048	.100	.114	.379	−0.123	0.322	
Age	-.082	-.008	.005	.103	−0.017	0.002	
Children	.132	.444	.181	.014	0.090	0.798	
Work Performance (Z_1)							0.044
Videoconferencing Tools (X)	.047	.110	.115	.340	−0.116	0.337	
Cognitive Overload (Y)	.155	.174	.059	.003	0.059	0.289	
Cognitive Overload * Digital Detox (M)	-.038	-.039	.055	.478	−0.147	0.069	
Digital Detox	.014	.020	.071	.773	−0.119	0.160	
Age	-.095	-.010	.005	.067	−0.020	0.001	
Children[a]	-.017	.-.062	.178	.727	−0.411	0.287	
Demands (Z_2)							0.167
Videoconferencing Tools (X)	.013	.027	.105	.795	−0.178	0.233	
Cognitive Overload (Y)	.262	.271	.049	<.001	0.175	0.367	
Cognitive Overload * Digital Detox (M)	-.116	-.111	.042	.008	−0.193	−0.029	
Digital Detox	.002	.002	.062	.927	−0.119	0.123	
Age	-.149	-.014	.004	.001	−0.022	−0.006	
Children	.216	.751	.176	<.001	0.406	1.097	
Loss of Joy (Z_3)							0.049
Videoconferencing Tools (X)	.043	.075	.089	.397	−0.099	0.249	
Cognitive Overload (Y)	.197	.164	.041	<.001	0.084	0.245	
Cognitive Overload * Digital Detox (M)	-.044	-.034	.049	.402	−0.112	0.045	
Digital Detox	-.065	-.068	.052	.192	−0.171	0.034	
Age	-.025	-.002	.004	.640	−0.010	0.006	
Children	-.039	-.108	.145	.453	−0.392	0.175	
Tension (Z_4)							0.085
Videoconferencing Tools (X)	.006	.013	.115	.912	−0.213	0.239	
Cognitive Overload (Y)	.202	.209	.052	<.001	0.108	0.310	
Cognitive Overload * Digital Detox (M)	-.078	-.075	.050	.135	−0.174	0.023	
Digital Detox	.005	.007	.067	.921	−0.124	0.137	
Age	-.167	-.016	.005	.001	−0.025	−0.007	
Children	.043	.150	.177	.396	−0.196	0.497	
Worries (Z_5)							0.144
Videoconferencing Tools (X)	-.026	-.053	.101	.601	−0.251	0.145	
Cognitive Overload (Y)	.242	.239	.049	<.001	0.143	0.334	
Cognitive Overload * Digital Detox (M)	-.074	-.067	.048	.157	−0.161	0.026	
Digital Detox	-.049	.062	.059	.297	−0.178	0.055	
Age	-.271	-.024	.004	<.001	−0.033	−0.016	
Children	-.001	-.004	.161	.979	−0.312	0.320	
Indirect &Total Effects							
Ind1 ($X \rightarrow Y \rightarrow Z_1$)	.007	.017	.021	.400	−0.023	0.058	
Ind2 ($X \rightarrow Y \rightarrow Z_2$)	.013	.027	.031	.385	−0.034	0.088	
Ind3 ($X \rightarrow Y \rightarrow Z_3$)	.009	.016	.019	.389	−0.021	0.054	
Ind4 ($X \rightarrow Y \rightarrow Z_4$)	.010	.021	.024	.387	−0.026	0.068	
Ind5 ($X \rightarrow Y \rightarrow Z_5$)	.012	.024	.027	.382	−0.030	0.077	
Total Effect 1	.055	.128	.117	.277	−0.102	0.358	
Total Effect 2	.025	.054	.105	.606	−0.152	0.261	
Total Effect 3	.053	.092	.092	.318	−0.088	0.271	
Total Effect 4	.016	.034	.117	.773	−0.195	0.262	
Total Effect 5	-.014	-.029	.105	.781	−0.234	0.176	
Overall Total Effect	.134	.278	.367	.449	−0.441	0.997	

Notes:
[a] 0 = no children in household; Confidence intervals for conditional indirect effects are bias-corrected; Number of bootstrap samples: 5000.

the character of communication. Via videoconferences not only verbal but also nonverbal (e.g., facial expressions, gestures) and paraverbal (e.g., intonation, prosody) information are transmitted. Especially nonverbal and paraverbal information facilitate relational links among team members, which may foster the effectiveness of information exchange and satisfaction with the communication situation (e.g., Warkentin, Sayeed, & Hightower, 1997). Text-based communication, in turn, opens a wide latitude for interpretation of persons' "true" meaning behind their words. Further, it is a challenging task to extract emotions from written text (Mahajan & Zaveri, 2020; Riordan & Kreuz, 2010).

As accumulating asynchronous text-based communication may lead to feelings of stress and overload, future research should focus on an adequate trade-off between the productive use of text-based digital tools and, for example, the establishment of time slots during which employees are not receiving any more tasks that could pile up on their (virtual) desks (also see Lüthje & Thiele, 2020). Another important difference is that synchronous communication tends to be more time constrained than asynchronous, meaning that there usually are predefined time slots for video calls, whereas messages in text-based tools can often be posted and read at any time.

In the present study, perceptions of cognitive overload were related to different facets of well-being, independently from the digital tool used. In line with previous findings, feeling overloaded was associated with negative indicators of well-being, such as worries, tensions and loss of joy (see e.g., Eppler & Mengis, 2004). Contrary to prior expectations, there was a *positive* relationship between cognitive overload and subjective work performance—but only for people who used videoconferencing tools at least as often as before the pandemic. This may be because the feeling of being forced to work harder and faster also increased the perception of working more efficiently. These

Table 4
Coefficients and conditional indirect effects for Model 2: Text-based tools (n = 258).

Regressions	β	*b*	*SE*	*p*	95% CI Lower Bound	95% CI Upper Bound	R^2
Cognitive Overload							.050
Text-based Tools (X)	.158	.259	.098	.008	0.067	0.450	
Age	-.040	-.004	.006	.537	−0.016	0.008	
Children	.153	.507	.233	.030	0.050	0.963	
Work Performance (Z_1)							.013
Text-based Tools (X)	.038	.068	.121	.574	−0.170	0.306	
Cognitive Overload (Y)	-.005	-.006	.071	.934	−0.145	0.133	
Cognitive Overload * Digital Detox (M)	-.042	-.040	.065	.535	−0.167	0.087	
Digital Detox	-.030	-.041	.089	.647	−0.216	0.134	
Age	-.079	-.008	.007	.231	−0.021	0.005	
Children[a]	-.041	-.150	.211	.476	−0.563	0.263	
Demands (Z_2)							.179
Text-based Tools (X)	.093	.151	.096	.117	−0.038	0.340	
Cognitive Overload (Y)	.267	.265	.059	<.001	0.149	0.381	
Cognitive Overload * Digital Detox (M)	-.101	-.088	.049	.072	−0.185	0.008	
Digital Detox	-.018	-.022	.078	.773	−0.175	0.130	
Age	-.076	-.007	.006	.214	−0.019	0.004	
Children	.234	.772	.218	<.001	0.345	1.199	
Loss of Joy (Z_3)							.067
Text-based Tools (X)	-.003	-.003	.081	.967	−0.162	0.156	
Cognitive Overload (Y)	.214	.172	.050	.001	0.074	0.271	
Cognitive Overload * Digital Detox (M)	-.097	-.069	.048	.150	−0.163	0.025	
Digital Detox	-.008	-.008	.064	.896	−0.135	0.118	
Age	-.089	-.007	.005	.165	−0.016	0.003	
Children	-.054	-.146	.164	.374	−0.467	0.0′176	
Tension (Z_4)							.098
Text-based Tools (X)	-.052	-.083	.097	.387	−0.273	0.106	
Cognitive Overload (Y)	.209	.205	.063	.001	0.082	0.328	
Cognitive Overload * Digital Detox (M)	-.118	-.102	.061	.096	−0.222	0.018	
Digital Detox	.016	.020	.083	.810	−0.142	0.182	
Age	-.183	-.017	.006	.003	−0.029	−0.006	
Children	.068	.220	.216	.308	−0.203	0.643	
Worries (Z_5)							.163
Text-based Tools (X)	-.006	-.010	.096	.913	−0.198	0.177	
Cognitive Overload (Y)	.236	.231	.063	<.001	0.109	0.355	
Cognitive Overload * Digital Detox (M)	-.117	-.102	.062	.098	−0.223	0.019	
Digital Detox	-.089	-.110	.062	.129	−0.251	0.032	
Age	-.291	-.027	.006	<.001	−0.039	−0.016	
Children	-.007	-.023	.205	.912	−0.425	0.379	

Table 4 (*continued*)

Regressions	β	*b*	*SE*	*p*	95% CI Lower Bound	95% CI Upper Bound	R^2
Indirect & Total Effects							
Ind1 ($X \rightarrow Y \rightarrow Z_1$)	-.001	-.002	.018	.934	−0.038	0.035	
Ind2 ($X \rightarrow Y \rightarrow Z_2$)	.042	.069	.030	.024	0.009	0.128	
Ind3 ($X \rightarrow Y \rightarrow Z_3$)	.034	.045	.033	.043	0.001	0.088	
Ind4 ($X \rightarrow Y \rightarrow Z_4$)	.033	.053	.026	.038	0.003	0.103	
Ind5 ($X \rightarrow Y \rightarrow Z_5$)	.037	.060	.028	.033	0.005	0.115	
Total Effect 1	.037	.067	.120	.580	−0.169	0.303	
Total Effect 2	.135	.220	.097	.024	0.030	0.410	
Total Effect 3	.031	.041	.081	.611	−0.118	0.200	
Total Effect 4	-.019	-.030	.097	.754	−0.221	0.160	
Total Effect 5	.031	.050	.097	.609	−0.140	0.239	
Overall Total Effect	.215	.347	.342	.284	−0.288	0.981	

Notes:
[a] 0 = no children in household; Confidence intervals for conditional indirect effects are bias-corrected; Number of bootstrap samples: 5000.

relationships were not found for text-based tools, suggesting that —at least from the respondents' point of view—work performance did not suffer from the digital working environments and a potential digital overload associated with them.

The relationship between cognitive overload and demands was moderated by the number of digital detox measures for people reporting more frequent use of videoconferencing tools during the pandemic. The more "non-digital" tasks people apply in order to avoid or recover from digital stress and overload, the weaker is the association between feelings of cognitive overload and perception of demands (e.g., time pressure, workload). This relationship was not found for text-based tools and other outcome variables.

7. Limitations and future research

First and foremost, it is important to note that causal relationships cannot be inferred from the single administration of a survey. Disentangling the causal relationships between the variables investigated requires longitudinal or experimental research. Moreover, the sample is limited as participants stem mostly from a non-probability sample. Partly, the sample is a convenience sample. Consequently, there may be sampling bias, for example, in that persons with interests or affinities for digital technology were more likely to participate in the study.

Another limitation of the study is that statements about the specific usefulness of different digital detox strategies for different platforms and dimensions of well-being are not possible. Although participants were asked openly to name their digital detox strategies, the sample size was insufficient to analyse the potential moderating effect of different strategy types. Differentiating between digital detox strategies regarding their potential moderating role might be an interesting avenue for future research looking at the effectiveness of specific digital detox measures (see e.g., Schmuck, 2020).

Future research should also examine further potentially relevant additional covariates, such as digital literacy, general job satisfaction, and work motivation, which have been shown to be important variables in previous research (e.g., Bucher, Fieseler, & Suphan, 2013). It would, for example, be interesting to investigate the role technical expertise might have in the relationships investigated in this study. It could be expected that the challenges of digital work tools are greater for those technologically less savvy. Moreover, the present study measured perceptions, not actual behaviours. So actual increases or decreases in

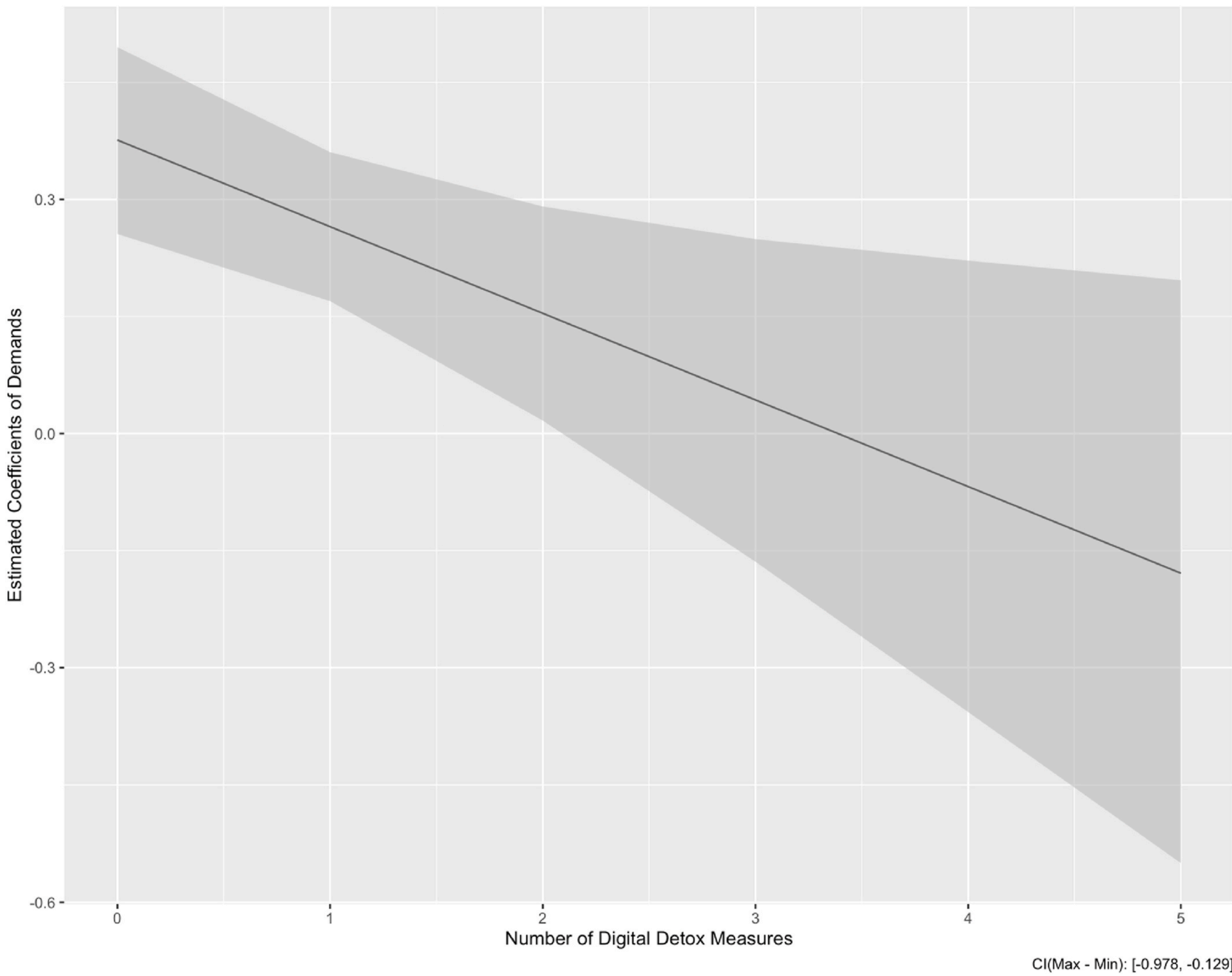

Fig. 2. Plot of changes in the estimated coefficients (unstandardized) for the regression of the dependent variable (demands) on the independent variable (digital overload) at different levels of the moderator (digital detox measures) for Model 1; gray area indicates the 95% CI.

cognitive overload, well-being, subjective work performance, or whether people applied more diverse digital detox measures than before the pandemic are unknown and could be addressed, for example, in the context of ethnographic or field studies or via experience sampling (also known as momentary assessment) methods.

8. Conclusion and practical implications

Overall, this research offers some insight into a scenario where working environments are quickly and comprehensively digitized. While this scenario was somewhat forced by measures against the COVID-19 pandemic, many companies aim at digitizing their employees' work and allowing more work from home. Until now, research suggests that organizational approaches, such as providing a supportive environment or restricting working hours, only show mixed effects on employees' productivity, satisfaction, and stress level (Nurmi, 2011; Savage & Staunton, 2018). Hence, other measures may be needed to ensure a healthy and productive digital work life.

Three main practical implications can be derived from the results of this study: 1) Organizations should rely on synchronous, audio-visual work tools (instead of asynchronous text-based tools) to the extent possible (Petrova & Schulz, 2021). 2) Organizations should make sure that all tools are easy to use and standardize on a limited number of tools (if possible). 3) It may be worthwhile to encourage digital detox behaviors.

Statement

JBS, TW, and JB contributed in equal proportions to study conception and data collection. JBS analysed and interpreted the data and drafted the article. TW and JB revised it critically for important intellectual content.

Funding

The authors have no funding to disclose.

Compliance with ethical standards

The research presented in this paper has been conducted in compliance with the APA Ethics Code.

Informed consent

Informed consent was obtained from all participants included in the study.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2021.106899.

References

Bawden, D., & Robinson, L. (2009). The dark side of information: Overload, anxiety and other paradoxes and pathologies. *Journal of Information Science, 35*(2), 180–191. https://doi.org/10.1177/0165551508095781

Becker, M. W., Alzahabi, R., & Hopwood, C. J. (2013). Media multitasking is associated with symptoms of depression and social anxiety. *Cyberpsychology, Behavior, and Social Networking, 16*, 132–135. https://doi.org/10.1089/cyber.2012.0291

Bitkom. (2020). *Corona-Pandemie: Arbeit im Homeoffice nimmt deutlich zu [Corona pandemic: Telework increases significantly]*. Retrieved from https://www.bitkom.org/Presse/Presseinformation/Corona-Pandemie-Arbeit-im-Homeoffice-nimmt-deutlich-zu.

Bucher, E., Fieseler, C., & Suphan, A. (2013). The stress potential of social media in the workplace. *Information, Communication & Society, 16*, 1639–1667. https://doi.org/10.1080/1369118X.2012.710245

Carrigan, M., & Duberley, J. (2013). Time triage: Exploring the temporal strategies that support entrepreneurship and motherhood. *Time & Society, 22*, 92–118. https://doi.org/10.1177/0961463X11402314

Chen, C.-Y., Pedersen, S., & Murphy, K. L. (2011). Learners' perceived information overload in online learning via computer-mediated communication. *Research in Learning Technology, 19*, 101–116. https://doi.org/10.1080/21567069.2011.586678

Choi, S. B., & Lim, M. S. (2016). Effects of social and technology overload on psychological well-being in young South Korean adults: The mediatory role of social network service addiction. *Computers in Human Behavior, 61*, 245–254. https://doi.org/10.1016/j.chb.2016.03.032

De Jonge, J., Spoor, E., Sonnentag, S., Dormann, C., & van den Tooren, M. (2012). "Take a break?!" Off-job recovery, job demands, and job resources as predictors of health, active learning, and creativity. *European Journal of Work & Organizational Psychology, 21*, 321–348. https://doi.org/10.1080/1359432x.2011.576009

De', R., Pandey, N., & Pal, A. (2020). Impact of digital surge during covid-19 pandemic: A viewpoint on research and practice. Advance online publication *International Journal of Information Management*. , Article 102171. https://doi.org/10.1016/j.ijinfomgt.2020.102171.

Eisinga, R., Grotenhuis, M. T., & Pelzer, B. (2013). The reliability of a two-item scale: Pearson, Cronbach, or Spearman-Brown? *International Journal of Public Health, 58*(4), 637–642. https://doi.org/10.1007/s00038-012-0416-3

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society, 20*, 325–344. https://doi.org/10.1080/01972240490507974

Eurofound and the International Labour Office. (2017). *Digital age. Further exploring the working conditions of ICT-based mobile workers and home-based teleworkers*. Retrieved from https://www.eurofound.europa.eu/sites/default/files/wpef18007.pdf.

Fliege, H., Rose, M., Arck, P., Levenstein, S., & Klapp, B. F. (2009). PSQ. Perceived stress questionnaire. In , *Elektronisches testarchiv. Trier: ZPIDLeibniz-Zentrum für psychologische Information und dokumentation (ZPID)*. https://doi.org/10.23668/psycharchives.351

van Gog, T., Paas, F., & Sweller, J. (2010). Cognitive load theory: Advances in research on worked examples, animations, and cognitive load measurement. *Educational Psychology Review, 22*, 375–378. https://doi.org/10.1007/s10648-010-9145-4

Haufe. (2020). *Mitarbeiter im Homeoffice befürchten einen Karriereknick [Employees working from home fear career setback]*. Retrieved from https://www.haufe.de/personal/hr-management/studie-homeoffice-in-der-corona-krise-vergleich-zum-buero_80_516216.html.

Jiang, D., Kalyuga, S., & Sweller, J. (2020). Comparing face-to-face and computer-mediated collaboration when teaching EFL writing skills. *Educational Psychology*. https://doi.org/10.1080/01443410.2020.1785399

Karr-Wisniewski, P., & Lu, Y. (2010). When more is too much: Operationalizing technology overload and exploring its impact on knowledge worker productivity. *Computers in Human Behavior, 26*, 1061–1072. https://doi.org/10.1016/j.chb.2010.03.008

Kushlev, K., & Dunn, E. W. (2015). Research Report: Checking email less frequently reduces stress. *Computers in Human Behavior, 43*, 220–228. https://doi.org/10.1016/j.chb.2014.11.005

Lanaj, K., Johnson, R., & Barnes, C. (2014). Beginning the workday yet already depleted? Consequences of late- night smartphone use and sleep. *Organizational Behavior and Human Decision Processes, 124*(1), 11–23. https://doi.org/10.1016/j.obhdp.2014.01.001

Lee, A. R., Son, S.-M., & Kim, K. K. (2016). Information and communication technology overload and social networking service fatigue: A stress perspective. *Computers in Human Behavior, 55*, 51–61. https://doi.org/10.1016/j.chb.2015.08.011

Leiner, D. J. (2016). Our research's breadth lives on convenience samples A case study of the online respondent pool "SoSci Panel. *Studies in Communication | Media, 5*(4), 367–396. https://doi.org/10.5771/2192-4007-2016-4-367

Lüthje, C., & Thiele, F. (2020). Communication floods – emails in scholarly communication. *Studies in Communication and Media, 9*, 367–393. https://doi.org/10.5771/2192-4007-2020-3-367

Mahajan, R., & Zaveri, M. (2020). Humor identification using affect based content in target text. *Journal of Intelligent and Fuzzy Systems*, 1–12. https://doi.org/10.3233/jifs-191648

Matthes, J., Karsay, K., Schmuck, D., & Stevic, A. (2020). "Too much to handle" - impact of mobile social networking sites on information overload, depressive symptoms, and well-being. *Computers in human behavior*. Advanced online publication. https://doi.org/10.1016/j.chb.2019.106217

Newport, C. (2019). *Digital minimalism: Choosing a focused life in a noisy world*. New York: Portfolio/Penguin.

Nurmi, N. (2011). Coping with coping strategies: How distributed teams and their members deal with the stress of distance, time zones and culture. *Stress and Health, 27*, 123–143. https://doi.org/10.1002/smi.1327

Petrova, K., & Schulz, M. (2021). Emotional experiences in digitally mediated and in-person interactions: An experience-sampling study. *PsyArXiv*. https://doi.org/10.31234/osf.io/2teu5

R Core Team. (2020). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Reinecke, L., Aufenanger, S., Beutel, M. E., Dreier, M., Quiring, O., & Müller, K. W. (2017). Digital stress over the life span: The effects of communication load and internet multitasking on perceived stress and psychological health impairments in a German probability sample. *Media Psychology, 20*, 90–115. https://doi.org/10.1080/15213269.2015.1121832

Riordan, M. A., & Kreuz, R. J. (2010). Emotion encoding and interpretation in computer-mediated communication: Reasons for use. *Computers in Human Behavior, 26*(6), 1667–1673. https://doi.org/10.1016/j.chb.2010.06.015

Rosseel, Y. (2012). lavaan: An R package for structural Equation modeling. *Journal of Statistical Software, 48*(2). https://doi.org/10.18637/jss.v048.i02

Savage, R., & Staunton, M. (2018). How employees are impacted. In P. Thomson, M. Johnson, & J. Devlin (Eds.), *Conquering digital overload (9-24)*. Cham: Palgrave Macmillan.

Schmitt, J. B., Debbelt, C. A., & Schneider, F. M. (2017). Too much information? – predictors of information overload in the context of online-news exposure. *Information, Communication & Society, 21*, 1151–1167. https://doi.org/10.1080/1369118X.2017.1305427

Schmuck, D. (2020). Does digital detox work? Exploring the role of digital detox applications for problematic smartphone use and well-being of young adults using multigroup analysis. *Cyberpsychology, behavior and social networking*. Advance online publication. https://doi.org/10.1089/cyber.2019.0578

Shepherd-Banigan, M., Bell, J. F., Basu, A., Booth-LaForce, C., & Harris, J. R. (2016). Workplace stress and working from home influence depressive symptoms among employed women with young children. *International Journal of Behavioral Medicine, 23*, 102–111. https://doi.org/10.1007/s12529-015-9482-2

Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction, 4*, 293–312. https://doi.org/10.1016/0959-4752(94)90003-5

Syvertsen, T., & Enli, G. (2019). *Digital detox: Media resistance and the promise of authenticity*. *Convergence*. The International Journal of Research into New Media Technologies. https://doi.org/10.1177/1354856519847325

Tarafdar, M., Tu, Q., & Ragu-Nathan, T. S. (2010). Impact of technostress on end-user satisfaction and performance. *Journal of Management Information Systems, 27*, 303–334. https://doi.org/10.2753/mis0742-1222270311

Vorderer, P., Hefner, D., Reinecke, L., & Klimmt, C. (Eds.). (2017). *Permanently online, permanently connected: Living and communicating in a POPC World*. London: Routledge.

Warkentin, M. E., Sayeed, L., & Hightower, R. (1997). Virtual teams versus face-to-face teams: An Exploratory study of a web-based conference system. *Decision Sciences, 28*(4), 975–996. https://doi.org/10.1111/j.1540-5915.1997.tb01338.x

Zumbach, J. (2006). Cognitive overhead in hypertext learning reexamined: Overcoming the myths. *Journal of Educational Multimedia and Hypermedia, 15*(4), 411–432.

Zumbach, J., & Mohraz, M. (2008). Cognitive load in hypermedia reading comprehension: Influence of text type and linearity. *Computers in Human Behavior, 24*(3), 875–887. https://doi.org/10.1016/j.chb.2007.02.015