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

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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,
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 overload (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 (Haute, 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) (Haute, 2020). Importantly, in such situations, the division between work and non-work is less bounded by clear temporal and physical markers (Carrigan & Duberley, 2013; Lithjé & 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, Dorschm, & 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.
4. Methods

4.1. Sample

The data used in this analysis originates from a more comprehensive online survey created with SocSci Survey 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. Thus, the final sample consisted of N = 403 respondents, age 18-87 years (M_age = 38.93, SD_age = 17.49; n_male = 259, n_female = 141, n_non-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.

4.2. 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).

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 effectively 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).

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.

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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   |

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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).
4.2.5. Well-being

Well-being was measured with the ‘Perceived Stress Questionnaire (PSQ-20)’ (Filege, 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 [-.012, 0.322], β = .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], β = .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 (.059, .289), β = .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 2

| 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”                                                  |
| Homework/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/Mindfulness                               | 3     | “I track down what I ‘really’ need”                                            |
| Ignoring links                                       | 1     | “I do not open links people send me”                                           |
| Nothing                                              | 58    |                                                                               |
| Sum                                                  | 403   |                                                                               |
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 but also nonverbal (e.g., facial expressions, gestures) and paraverbal (e.g., intonation, prosody) information are transmitted. Especially but also nonverbal (e.g., facial expressions, gestures) and paraverbal (e.g., intonation, prosody) information are transmitted. Especially

| Table 3 Coefficients and conditional indirect effects for Model 1: Videoconferencing tools (n = 395). |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| Regressions     | β               | b               | SE              | p               |
| Cognitive Overload | .048            | .100            | .114            | .379            |
| Videoconferencing Tools (X) | .047            | .110            | .115            | .340            |
| Cognitive Overload (Y) | .155            | .174            | .059            | .003            |
| Cognitive Overload * Digital Detox (M) | -.038            | -.039            | -.055            | .478            |
| Digital Detox | .014            | .020            | .071            | .773            |
| Age             | -.095            | -.010            | .005            | .067            |
| Children⁸      | -.017            | -.062            | -.178            | .727            |
| Work Performance (Z₁) | .132            | .444            | .181            | .014            |
| Cognitive Overload (Y) | .262            | .271            | .049            | <.001           |
| Cognitive Overload * Digital Detox (M) | -.116            | -.111            | .042            | .008            |
| Digital Detox | .002            | .002            | .062            | .927            |
| Age             | -.149            | -.014            | .004            | .001            |
| Children⁸      | .216            | .751            | .176            | <.001           |
| Loss of Joy (Z₂) | .013            | .027            | .105            | .795            |
| Cognitive Overload (Y) | .197            | .164            | .041            | <.001           |
| Cognitive Overload * Digital Detox (M) | -.044            | -.034            | .049            | .402            |
| Digital Detox | -.065            | -.068            | .052            | .192            |
| Age             | -.025            | -.002            | .004            | .640            |
| Children⁸      | -.039            | -.108            | .145            | .453            |
| Tension (Z₃)   | .006            | .013            | .115            | .912            |
| Cognitive Overload (Y) | .202            | .209            | .052            | <.001           |
| Cognitive Overload * Digital Detox (M) | -.078            | -.075            | .050            | .135            |
| Digital Detox | .005            | .007            | .067            | .921            |
| Age             | -.167            | -.016            | .005            | .001            |
| Children⁸      | .043            | .150            | .177            | .396            |
| Worries (Z₄)   | -.026            | -.053            | .101            | .601            |
| Cognitive Overload (Y) | .242            | .239            | .049            | <.001           |
| Cognitive Overload * Digital Detox (M) | -.074            | -.067            | .048            | .157            |
| Digital Detox | -.049            | -.062            | .059            | .297            |
| Age             | -.271            | -.024            | .004            | <.001           |
| Children⁸      | -.001            | -.004            | .161            | .979            |
| Indirect & Total Effects | .007            | .017            | .021            | .400            |
| Ind1 (X → Y → Z₁) | .013            | .027            | .031            | .385            |
| Ind2 (X → Y → Z₂) | .009            | .016            | .019            | .389            |
| Ind3 (X → Y → Z₃) | .010            | .021            | .024            | .387            |
| Ind4 (X → Y → Z₄) | .012            | .024            | .027            | .382            |
| Total Effect 1 | .055            | .128            | .117            | .277            |
| Total Effect 2 | .025            | .054            | .105            | .606            |
| Total Effect 3 | .053            | .092            | .092            | .318            |
| Total Effect 4 | .016            | .034            | .117            | .773            |
| Total Effect 5 | -.014            | -.029            | .105            | .781            |
| Overall Total Effect | .134            | .278            | .367            | .449            |
| 95% CI Lower Bound | -.001            | -.004            | .161            | .979            |
| 95% CI Upper Bound | -.023            | -.002            | .400            | .385            |
| R²             | .007            | .017            | .021            | .400            |
|               | .013            | .027            | .031            | .385            |
|               | .009            | .016            | .019            | .389            |
|               | .010            | .021            | .024            | .387            |
|               | .012            | .024            | .027            | .382            |
|               | .055            | .128            | .117            | .277            |
|               | .025            | .054            | .105            | .606            |
|               | .053            | .092            | .092            | .318            |
|               | .016            | .034            | .117            | .773            |
|               | -.014            | -.029            | .105            | .781            |
|               | .134            | .278            | .367            | .449            |

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

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 pre-defined 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., Sippler & 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 | 95% CI Upper | R²  |
|----------------------|------|-------|------|-------|--------------|--------------|-----|
| Cognitive Overload   |      |       |      |       |              |              | .050|
| Text-based Tools (X) | .158 | .259  | .098 | .008  | .067         | .450         |     |
| Age                  | -.040| -.004 | .006 | .537  | -.016        | .008         |     |
| Children             | .153 | .507  | .233 | .030  | .050         | .963         |     |
| Work Performance (Z1)|      |       |      |       |              |              | .133|
| Text-based Tools (X) | .038 | .068  | .121 | .574  | -.170        | .306         |     |
| Cognitive Overload   |      |       |      |       |              |              |     |
| Cognitive Overload * | -.042| -.040 | .065 | .535  | -.167        | .087         |     |
| Digital Detox (M)    |      |       |      |       |              |              |     |
| Loss of Joy (Z2)     |      |       |      |       |              |              | .179|
| Text-based Tools (X) | .093 | .151  | .096 | .117  | -.038        | .340         |     |
| Cognitive Overload (Y)|  .267| .265  | .059 | <.001 | .149         | .381         |     |
| Cognitive Overload * | -.101| -.088 | .049 | .072  | -.185        | .008         |     |
| Digital Detox (M)    |      |       |      |       |              |              |     |
| Loss of Joy (Z1)     |      |       |      |       |              |              | .067|
| Text-based Tools (X) | .003 | .003  | .081 | .967  | -.162        | .156         |     |
| Cognitive Overload (Y)|  .214| .172  | .050 | .001  | .074         | .271         |     |
| Cognitive Overload * | -.097| -.069 | .048 | .150  | -.163        | .025         |     |
| Digital Detox (M)    |      |       |      |       |              |              |     |
| Loss of Joy (Z1)     |      |       |      |       |              |              | .098|
| Text-based Tools (X) | .052 | .083  | .097 | .387  | -.273        | .106         |     |
| Cognitive Overload (Y)|  .209| .205  | .063 | .001  | .082         | .328         |     |
| Cognitive Overload * | -.118| -.102 | .061 | .096  | -.222        | .018         |     |

Table 4 (continued)

| Regressions          | β    | b     | SE   | p     | 95% CI Lower | 95% CI Upper | R²  |
|----------------------|------|-------|------|-------|--------------|--------------|-----|
| Indirect &           |      |       |      |       |              |              |     |
| Total Effects        |      |       |      |       |              |              |     |
| Ind1 (X → Y)         | -.001| -.002 | .018 | .934  | -.038        | .035         |     |
| Ind2 (X → Y)         | .042 | .069  | .030 | .024  | .009         | .128         |     |
| Ind3 (X → Y)         | .034 | .045  | .033 | .043  | .001         | .088         |     |
| Ind4 (X → Y)         | .033 | .053  | .026 | .038  | .003         | .103         |     |
| Ind5 (X → Y)         | .037 | .060  | .028 | .033  | .005         | .115         |     |
| Total Effect 1       | .037 | .067  | .120 | .580  | -.169        | .303         |     |
| Total Effect 2       | .135 | .220  | .097 | .024  | .030         | .410         |     |
| Total Effect 3       | .031 | .041  | .081 | .611  | -.118        | .200         |     |
| Total Effect 4       | -.019| -.030 | .097 | .754  | -.221        | .160         |     |
| Total Effect 5       | .031 | .050  | .097 | .699  | -.140        | .239         |     |
| Overall Total        | .215 | .347  | .342 | .284  | -.288        | .981         |     |

Notes:
* 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
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. 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.

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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.
