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Published in:
Journal of Occupational Health Psychology

DOI:
10.1037/ocp0000362

Published: 01/12/2023

Document Version
Publisher's PDF, also known as Version of record

Please cite the original version:
Nurmi, N., & Pakarinen, S. (2023). Virtual Meeting Fatigue: Exploring the Impact of Virtual Meetings on Cognitive Performance and Active Versus Passive Fatigue. *Journal of Occupational Health Psychology*, *28*(6), 343-362. https://doi.org/10.1037/ocp0000362

AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Occupational Health Psychology

ISSN: 1076-8998

2023, Vol. 28, No. 6, 343–362
https://doi.org/10.1037/ocp0000362

Virtual Meeting Fatigue: Exploring the Impact of Virtual Meetings on Cognitive Performance and Active Versus Passive Fatigue

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In this study, we challenge the commonly held belief that virtual meeting fatigue manifests as exhaustion (i.e., active fatigue) resulting from overloading demands and instead suggest that participation in virtual meetings may lead to increased drowsiness (i.e., passive fatigue) due to underload of stimulation. Using subjective and cardiac measures (heart rate variability), we investigated the relationships between virtual versus face-to-face meetings and different types of fatigue (active and passive) among 44 knowledge workers during real-life meetings ($N = 382$). Our multilevel path analysis revealed a link between virtual meetings and higher levels of passive fatigue, which then impacted cognitive performance. Additionally, our results suggest that work engagement may act as an individual-level moderator, explaining why some knowledge workers are affected, while others are not. Given the growing amount of time spent in virtual meetings, these findings emphasize the risks to mental energy and cognitive performance and highlight the protective role of high general work engagement.

Keywords: meetings, fatigue, heart rate variability, cognitive flexibility, virtual work

The widespread adoption of virtual work has drastically changed the way we interact and collaborate, with virtual meetings becoming the new norm for many organizations (Allen & Lehmann-Willenbrock, 2022; Hill et al., 2022). While virtual meetings have the advantage of allowing for remote work and reducing travel time, many knowledge workers have reported feelings of fatigue after participation in virtual meetings (Bennett et al., 2021; Shockley et al., 2021). This phenomenon has been referred to as "virtual meeting fatigue," "videoconference fatigue," or "Zoom fatigue" interchangeably in scientific and popular literature.

Scholars define virtual meeting fatigue as "the degree to which people feel exhausted or tired attributed to engaging in a videoconference" (Bennett et al., 2021, p. 330). Studies suggest that such fatigue may result from increased cognitive demands, when individuals are required to pay constant attention to the screen (Bennett et al., 2021), engage in continuous verbal and nonverbal communication (Bailenson, 2021), and be constantly presentable (e.g., Kuhn, 2022; Shockley et al., 2021). Cognitive psychologists categorize such fatigue state that derives from high-demand conditions as *active fatigue* (e.g., Desmond & Hancock, 2001; Saxby et al., 2013). While the existing research on meeting-related fatigue (e.g., Luong & Rogelberg, 2005), and virtual meeting fatigue in particular, has mainly focused on active fatigue, it is important to note that cognitive psychology research indicates that mental fatigue can also manifest as *passive fatigue*, that is, a state of drowsiness or sleepiness that derives from monotonous task environment and underload of demands (e.g., Manly et al., 1999; Saxby et al., 2013). In virtual meetings, underload may occur, for example, due to a lack of physical activity, reduced engagement in discussions, or the monotonous nature of the meetings. Despite the growing awareness of the problems of overload and active fatigue in virtual meetings, there is still a shortage of research on the role of underload and passive fatigue in the development of virtual meeting fatigue. This lack of research is concerning, as each type of fatigue state requires a unique coping approach. The implementation of strategies aimed at mitigating overload could have the unintended consequence of exacerbating passive fatigue, and the same applies in reverse. To better understand and manage meeting-related fatigue among knowledge workers, there is a need for increased clarity on the nature of fatigue experienced. Without a thorough understanding of both active and passive fatigue in the context of virtual meetings, organizations may not be equipped to effectively mitigate the negative effects of prolonged virtual interactions on their employees' wellbeing and performance.

This article was published Online First October 26, 2023.
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This work was supported by the Finnish Funding Agency for Innovation, Tekes (Grant No. 2201/31/2012 and Grant No. 2202/31/2012). The authors thank Johanna Koroma, Olli Jahkola, Merit Morikawa, Marianne Leinikka, and the research nurses of the Finnish Institute of Occupational Health for their assistance with data collection and data analysis. Additionally, the authors thank Matti Vartiainen, Kiti Müller, Minna Huotilainen, Harri Lindholm, and Jussi Virkkala for their valuable advice and support throughout this project.

While working on this article, the authors utilized the OpenAI GPT-3.5 model to enhance English grammar and text flow. The authors take full responsibility for the content presented in this publication.

Niina Nurmi played a lead role in data curation, formal analysis, funding acquisition, investigation, project administration, software, supervision, visualization, writing–original draft, and writing–review and editing and an equal role in conceptualization, methodology, resources, and validation. Satu Pakarinen played a supporting role in writing–original draft and an equal role in conceptualization, methodology, and resources.

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Responding to Allen and Lehmann-Willenbrock (2022) call for research on meeting modalities and well-being, this study aims at building a more nuanced understanding of meeting-related fatigue that knowledge workers may experience during virtual and face-to-face meetings. While previous studies on virtual meeting fatigue have mainly relied on subjective fatigue assessments, our research employs a unique approach by integrating cardiac monitoring (heart rate variability [HRV]) with subjective ratings to measure the active and passive fatigue of 44 knowledge workers during 382 real-life virtual and in-person meetings. Additionally, we explore the role of general work engagement (Bakker et al., 2005) as a potential moderating factor that could distinguish individuals who are more susceptible to meeting-related fatigue. The impact of active and passive fatigue on cognitive performance, in particular cognitive flexibility, is also examined through a cognitively challenging task-switching test administered after the meetings. The results of this study provide a more comprehensive understanding of the distinct types of meeting-related fatigue states, their impact on cognitive flexibility, and the factors that contribute to their occurrence. This understanding can help organizations tailor their approaches to fatigue management to address both active and passive fatigue, thereby enhancing employee wellbeing and optimizing performance in virtual meeting environments.

Our study advances the existing literature on meeting modalities and fatigue in three key ways: First, we utilize Desmond and Hancock's (2001) theory of cognitive fatigue to provide a new theoretical lens to understand different types of fatigue (active and passive fatigue) that may arise during virtual and face-to-face meetings, and how they influence cognitive flexibility. Our results challenge previous findings, revealing that knowledge workers are more likely to experience passive fatigue (i.e., drowsiness and underarousal) rather than active fatigue (i.e., high-stress arousal) during virtual meetings. In our data, passive fatigue and low arousal were more prevalent among knowledge workers with low work engagement, but not among those with higher engagement levels. This suggests that an intrinsic interest in the task at hand may help individuals with high work engagement to remain focused and vigilant during virtual meetings and avoid drowsiness. These findings contribute to the limited research on passive meeting-related fatigue by highlighting work engagement as a potential moderator in mitigating the negative impact of virtual meetings on cognitive performance.

Second, we assessed the participants' cognitive flexibility after different types of meetings and discovered that the passive fatigue, which increased during virtual meetings, but not during face-to-face meetings, decreased cognitive flexibility (i.e., led to higher error rates in task-switching tests) after the meetings. These results shed more light on earlier mixed findings related to the positive and negative performance effects of virtuality (e.g., Mesmer-Magnus et al., 2011; Raghuram et al., 2019), implying that high work engagement may help employees to sustain optimal levels of energetic arousal and cognitive flexibility in virtual work.

Third, we make a methodological contribution to the research on workplace fatigue in demonstrating that HRV can serve as a reliable and feasible biomarker of active and passive fatigue that could be used to record changes in arousal *in situ* with wearable cardiac activity measurements, without work obstruction. While most studies on fatigue have either relied on self-reports (that are often susceptible to biases) or measured arousal and cognitive performance in laboratory settings, we assessed fatigue with cardiac measures and the actual changes of cognitive flexibility in knowledge workers' natural work settings. In directly linking HRV measures with subjective fatigue ratings and field observations, our results contribute to validating HRV parameters as indicators of active and passive fatigue, making a significant methodological contribution to the organizational research on fatigue.

Virtual Meeting Fatigue

Meetings are defined as focused interactions of cognitive attention, planned or impromptu gatherings for a common purpose, whether at the same place or in different places (Romano & Nunamaker, 2001). Before the onset of the COVID-19 pandemic, research in the field of meeting science had mainly focused on face-to-face meetings (e.g., Allen et al., 2015; Lehmann-Willenbrock et al., 2013; Rogelberg et al., 2006). However, the emergence of the pandemic has sparked a new wave of research, particularly focusing on the psychological effects of virtual meetings, suggesting that virtual meetings might be more mentally taxing than other types of meetings and may lead to virtual meeting fatigue, or so-called "zoom fatigue" (e.g., Bailenson, 2021; Fauville et al., 2021a). Such fatigue is defined as a feeling of being exhausted and tired attributed to engaging in a virtual meeting (Bennett et al., 2021; Shockley et al., 2021). The theory of cognitive fatigue (Desmond & Hancock, 2001) explains, however, that exhaustion and tiredness refer to different types of fatigue, active and passive fatigue: *Active fatigue* (exhaustion, stress) results from effortful attention and participation in a challenging task, while *passive fatigue* (drowsiness, sleepiness) is typically triggered by low workload, passive, or monotonous tasks. To date, most of the research on workplace fatigue (for a review, see Gawron, 2016), and virtual meeting fatigue in particular (for a review, see Li & Yee, 2023), has primarily focused on active fatigue while neglecting passive fatigue.

Active fatigue may derive from an overload of information processing demands related to a task or environmental factors (Kahneman, 1973). In virtual meetings, using a camera, for example, is suggested to require additional cognitive processing (Hinds, 1999) and increase self-presentation demands (Shockley et al., 2021), creating conditions of overload and active fatigue. High frequency, long duration, and short breaks between virtual meetings may also increase experiences of active fatigue (Fauville et al., 2021a). Bailenson (2021) theorized that virtual meetings may pose greater demands on effortful attention due to fewer nonverbal cues, such as facial expressions, gaze, and gestures, making the transfer and interpretation of implicit knowledge more difficult and tiring for participants. Technological problems, such as time lag, low resolution, and audio failures, may further limit the richness of nonverbal cues in virtual meetings and make them difficult to perceive (Ebrahim et al., 2009). In comparison to face-to-face meetings, videoconferencing provides less synchronization of coordinated behaviors, limited nonverbal cues, and real-time feedback (Dennis et al., 2008) that may require increased exertion of mental effort. The multiperson screen in video calls also presents a challenge to the brain's central vision, requiring it to decode and sustain partial attention to multiple participants at once. Navigating such virtual environments puts a heavy reliance on cognitive resources to maintain directed attention and switch attention rapidly between different objects. However, the human capacity to direct attention is finite (Baddeley & Hitch, 1974), and prolonged use of this cognitive resource can lead to overload and active fatigue (Desmond & Hancock, 2001; Meijman, 1997).

Virtual meeting fatigue may, however, also result from an underload of demands and manifest as a state of drowsiness, that is, *passive fatigue* (Desmond & Hancock, 2001). The term drowsiness refers to a state of low mental alertness, a drop in physiological activity, and a subjectively sensed feeling of sleepiness (Tejero Gimeno et al., 2006). This can be caused by low demands for mental effort and participation as well as reduced physical mobility in virtual meetings. In such underload situations, attention to the task at hand and situational awareness may suffer, leading to a decreased ability to listen and respond quickly to unforeseen questions. Although a person may try to compensate for drowsiness by trying harder to focus on the meeting tasks, excreting such compensatory mental effort may lead to a state of passive fatigue in prolonged underload situations (Mulder, 1986).

Until now, the burgeoning research on virtual meeting fatigue has not differentiated between active and passive fatigue while primarily relying on self-reported measures of (active) fatigue and exhaustion (e.g., Bennett et al., 2021; Fauville et al., 2021a; Shockley et al., 2021; Nesher Shoshan & Wehrt, 2022). However, scholars recommend incorporating objective measures, such as cardiac monitoring or eye tracking, to differentiate between active and passive fatigue (Phillips, 2015) and minimize response bias (Akinola et al., 2019; Rosenman et al., 2011). Response bias is a well-known issue in social and behavioral studies that rely on self-reported data, resulting from factors such as social desirability bias, misunderstanding the measurement, and lack of conscious awareness. In addition, given that psychophysiological responses like fatigue typically occur below the level of conscious awareness, individuals may not accurately recall, or even recognize, how they felt in certain situations (Bechara et al., 1997), which may affect the quality of self-reported data. As knowledge workers are typically more focused on their work tasks than on their feelings during workdays, they may interpret their feelings afterward on the basis of task performance. Furthermore, individuals may often struggle to differentiate fatigue from related subjective experiences such as stress (Tepas & Price, 2000), anxiety (Lal & Craig, 2001), burnout (Huibers et al., 2003), or boredom (Scerbo, 2000), which may affect their self-reported data.

In light of these limitations, this study aims to provide a more comprehensive understanding of virtual meeting fatigue among knowledge workers. To achieve this goal, we use a combination of field observations, cardiac monitoring, and subjective evaluations to gain a more nuanced understanding of the various types and underlying causes of virtual meeting fatigue.

Measuring Active and Passive Fatigue With Cardiac Measures

Changes in cardiac activity, such as HRV (the variation in time between each heartbeat), have been closely linked with the subjective experience of specific psychophysiological states, such as stress, fatigue, sleepiness, and drowsiness (for reviews, see Burlacu et al., 2021; Lu et al., 2022). The beat-to-beat variations in heart rate are mainly produced and intensified through the interplay of the heart and brain, which occurs via the transmission of neural signals through the afferent and efferent pathways of the sympathetic and parasympathetic branches of the autonomic nervous system (ANS). Therefore, HRV is viewed as an indicator of neurocardiac activity that mirrors the interplay between the heart and brain, as well as the dynamics of the ANS.

Recent advances in cardiac monitoring and HRV analysis have provided organizational scholars with the ability to investigate the ANS activity that is responsible for the immediate control of visceral function, internal regulation, and adaptation to external demands and strains (e.g., Massaro & Pecchia, 2019; Parker et al., 2020). Typically, when a person experiences a physical or mental load, sympathetic activity increases (heart rate increases) and parasympathetic activity decreases (HRV decreases), improving the body's energy production and ability to cope with the demand (Malik et al., 1996). When the load is passed and a person rests, the parasympathetic activity increases (HRV increases) and returns the body to homeostasis. As sleep and rest are closely linked to the activities of the brain and heart, cardiac monitoring can be used to accurately detect the levels of drowsiness and sleepiness (Jung et al., 2014). Previous studies on fatigue have utilized analysis of different HRV parameters to examine both active and passive fatigue (i.e., stress and drowsiness) in laboratory settings, often among drivers (e.g., Buendia et al., 2019; Oron-Gilad & Ronen, 2007; Schmidt & Bullinger, 2019; Schmidt et al., 2011; Vicente et al., 2016). We aim to advance this research by combining cardiac measures with ethnographic field observations to gain a better understanding of different types of fatigue states that knowledge workers may experience in various work meetings.

Active fatigue can be measured as decreased HRV, which indicates elevated stress arousal characterized by an increase in sympathetic activity and a decrease in parasympathetic activity (Gordan et al., 2015). *Passive fatigue*, in contrast, can be measured by an increase in HRV, indicating relaxation or drowsiness, and characterized by decreased sympathetic activity and increased parasympathetic activity (Castaldo et al., 2015; Furman et al., 2008; Michail et al., 2008). HRV can be calculated in several ways based on the beat-to-beat changes in the heart rate, using frequency and time-domain measures (Kuusela et al., 2002; McCraty & Shaffer, 2015; Richman & Moorman, 2000; Malik et al., 1996). The present study uses both types of HRV parameters to measure active and passive fatigue.

Active fatigue, or increased stress arousal, can be measured, for example, with frequency-domain HRV parameters, such as the low-frequency (LF: 0.04–0.15 Hz) and high-frequency (HF: 0.15–0.4 Hz) bands, reflecting the sympathetic and parasympathetic control of heart rate, respectively (Vicente et al., 2016). Particularly, the LF to HF ratio (LF/HF) carries significant interpretive value in measuring stress arousal, representing the balance between the sympathetic and parasympathetic branches of the ANS. A high LF/HF ratio indicates a dominance of sympathetic activity (often associated with stress or active fatigue), while a low LF/HF ratio indicates a dominance of parasympathetic activity (often associated with relaxation, drowsiness, or passive fatigue; Matthews et al., 2019). Studies among soldiers, aviators, and emergency security workers, for example, have demonstrated that even minor levels of stress arousal can result in a noticeable increase in the LF/HF ratio, reflecting the body's response to stress (e.g., Delgado-Moreno et al., 2019; Dussault et al., 2009; Ghazali et al., 2018).

Passive fatigue, or increased drowsiness, can be measured, for example, with time-domain HRV parameters, such as the root-mean-squared standard deviation (RMSSD) of successive interbeat intervals. This parameter is known to be more stable and repeatable (e.g., Uusitalo et al., 2011) and less affected by breathing (Penttilä et al., 2001) than other types of HRV measures, offering reliable and meaningful insights into different fatigue states and recovery. Scholars have used RMSSD, for example, to study sleepiness and drowsiness (for a recent review, see Matuz et al., 2020), self-regulation (e.g., Zahn et al., 2016), and stress recovery (e.g., Loerbroks et al., 2010) . Most of these studies have been conducted in laboratories (e.g., Burlacu et al., 2021; Kaida et al., 2007) and a few in real-road driving studies (Buendia et al., 2019; Jung et al., 2014; Persson et al., 2020). Repeated HRV monitoring in office-based field studies, however, is still scarce. A notable exception is a field study by Parker et al. (2020), in which they measured 72 office workers' stress arousal regulation over 5 consecutive workdays using two HRV parameters—high-frequency HF and RMSSD. The results of their study showed a positive relationship between HRV at work and self-reported evening relaxation. To collect the cardiac data, the office workers wore portable heart rate recorders throughout the week, allowing the researchers to analyze their HRV levels over an extended period. This method enabled the researchers to obtain a comprehensive understanding of how the workers' stress levels fluctuated during the workweek and how HRV was linked to relaxation after work hours (Parker et al., 2020).

As Parker et al. (2020) study demonstrates, wearable and noninvasive cardiac monitoring devices represent a promising technology for studying employees' psychophysiological reactions and states, with the advantage of being comfortable and portable for use in organizational field settings and actual work. This improves the ecological validity of the measurements. Continuous cardiac measurements enable quantification of workers' psychological states during different tasks in an objective and unobtrusive way. However, because these measurements do not directly provide information on the valence of the arousal, that is, whether the increased arousal arises from positive energetic excitement or negative exhaustion, complementary data are needed for proper interpretation and face validity. These data have typically been collected with self-reports, where the participant provides self-assessments, for example, on their experienced levels of distress, effort, and task load (often measured with The National Aeronautics and Space Administration Task Load Index; Hart & Staveland, 1988) or sleepiness and drowsiness, that is, passive fatigue (e.g., Karolinska Sleepiness Scale [KSS]; Åkerstedt & Gillberg, 1990). Due to the intricate psychophysiological nature of fatigue, gaining a comprehensive understanding requires the measurement of both its psychological and physiological elements (Phillips, 2015). Therefore, in this study, we measured both cardiac (RMSSD and LF/HF) and self-report measures of passive fatigue (i.e., subjective drowsiness with KSS) to capture knowledge workers' different fatigue states during virtual versus face-to-face meetings. To investigate the specific type of fatigue (passive or active) that participants may experience during virtual meetings, we test two competing hypotheses:

> *Hypothesis 1* (*passive fatigue*): Participation in virtual (vs. face-to-face) meetings (a) increases subjective drowsiness, (b) increases HRV (RMSSD), and (c) decreases stress arousal (LF/HF).

> *Hypothesis 2* (*active fatigue*): Participation in virtual (vs. face-to-face) meetings (a) decreases subjective drowsiness, (b) decreases HRV (RMSSD), and (c) increases stress arousal (LF/HF).

Work Engagement as Individual-Level Moderator

It may be too simplistic to assume that participation in virtual meetings causes fatigue among all employees without considering individual or situational differences. For example, Fauville et al.'s (2021b) study on virtual meeting fatigue shows differences in active fatigue states between individuals from different gender, age, and personality trait groups. They found, for example, that female, younger, and more introverted individuals may experience more active fatigue when participating in virtual meetings than male, older, and extroverts. Workers who lack experience with technology may also experience more stress and overload than technologically savvy workers when required to attend virtual meetings (Olson et al., 2012). It has also been found that employees who rate communication technology as low in usefulness experience stronger negative affect and information overload when required to use virtual meeting technologies (Lee, 2016). Bennett et al. (2021) studied videoconference characteristics and found that participants' perceived active fatigue may be lower when the technology was highly compatible with one's environment (i.e., when they experience high sense of belonging with other meeting attendees) or they were able to reduce attentional demands or detach momentarily by managing technological choices (e.g., using mute when not speaking and turning off webcam to reduce pressure to look attentive and the number of stimuli on screen). Individuals also differ in their capability to process cognitive information at a given time (Kahneman, 1973; Navon & Gopher, 1979), and virtual meetings can present varying levels of challenge for individuals in regard to maintaining focus and handling communication demands. Some may struggle with these demands, while others might be better able to manage them efficiently. For example, if a meeting participant needs to focus on a task or discussion with little or no intrinsically motivational draw, passive fatigue may occur. Tasks that are perceived as fascinating, in contrast, may draw effortless attention that does not require cognitive effort and thus do not lead to fatigue (Kaplan & Berman, 2010). As individuals with high work engagement tend to be highly intrinsically motivated and to perceive work in a positive way (Bakker et al., 2014; Schaufeli et al., 2006), they may be less vulnerable to passive fatigue in meetings.

A further aim in this study, therefore, is to find out if work engagement helps participants to avoid drowsiness and maintain optimal levels of energetic arousal in virtual meetings. Engaged employees tend to have high levels of physical energy (vigor); they are enthusiastic about the content of their work (dedication) and so immersed in their activities that time seems to fly (absorption; Bakker & Demerouti, 2017). Although levels of work engagement may fluctuate daily, some individuals are more engaged than others across situations (Breevaart et al., 2012; Kim, Park, & Headrick, 2018). Employees with a generally high level of work engagement have been shown to cope better with daily job demands (e.g., Bakker et al., 2005; Xanthopoulou et al., 2007). As engaged employees are able to draw from larger resource reservoirs, they offer myriad benefits to an organization: They tend to demonstrate a stronger commitment to organizational success, forge tighter bonds with team members, cultivate more effective collaborative relationships, exhibit increased organizational citizenship behaviors, and yield higher quality results (e.g., Cowardin-Lee & Soyalp, 2011; Salanova et al., 2005). These contributions are frequently realized within the context of meetings.

Previous research in meeting science has demonstrated that several meeting-related factors, such as meeting effectiveness, satisfaction, size, and participant behaviors, can foster employees' work engagement beyond the meeting context (e.g., Allen, Lehmann-Willenbrock, & Rogelberg, 2018; Allen & Rogelberg, 2013; Allen, Reiter-Palmon, et al., 2018; Lehmann-Willenbrock et al., 2016; Yoerger et al., 2015). However, the impact of work engagement on meeting experiences and responses to different meeting modalities remains largely unexplored. Although there is a dearth of research on engagement's role in meeting-induced fatigue, it can be reasonably hypothesized that highly engaged employees are likely to maintain optimal stress arousal levels during virtual meetings. Their positive attitudes toward meetings and active participation (Kauffeld & Lehmann-Willenbrock, 2012) could potentially reduce passive fatigue during virtual meetings. Conversely, disengaged employees, who may perceive meetings negatively and find little value in them (Luong & Rogelberg, 2005), could be more likely to experience drowsiness and passive fatigue in virtual meeting contexts. Hence, we hypothesize that participation in virtual (vs. face-to-face) meetings is more weakly related to subjective drowsiness and objective passive fatigue (RMSSD) and more strongly related to energizing stress arousal (LF/HF) among those with high general work engagement.

> *Hypothesis 3:* Work engagement on the individual level will moderate the meeting-level relationship between participation in virtual (vs. face-to-face) meetings and (a) subjective drowsiness, (b) RMSSD, and (c) LF/HF, such that employees with higher levels of engagement will experience lower subjective drowsiness, lower RMSSD, and higher LF/HF.

The Effect of Fatigue on Cognitive Performance

Research suggests that cognitive performance is vulnerable to both passive and active fatigue (Tanaka et al., 2014) and benefits from moderate (so-called "optimal") levels of stress arousal (Lambourne & Tomporowski, 2010). Exhausted or actively fatigued workers (with high levels of stress arousal) self-report lower performance (Bakker & Heuven, 2006) and tend to receive lower performance ratings from supervisors, colleagues, and customers (Taris, 2006). Passively fatigued persons typically experience a loss of motivation and energy (Hockey, 1997), which may result in impaired task performance and/or the avoidance of activities that demand high levels of effort (Boksem et al., 2006; Boksem & Tops, 2008; Hopstaken et al., 2015; van der Linden et al., 2003). Such effects may linger after cognitively demanding situations such as meetings.

To investigate the impact of meeting-related fatigue on knowledge workers' cognitive performance, we assessed their postmeeting cognitive flexibility, that is, "the deployment of cognitive control resources to adapt to changes in events" (Honn et al., 2019, p. 191) after the observed meetings. Cognitive flexibility plays a crucial role in the performance of knowledge workers as it enables individuals to shift between different modes of thinking and process multiple concepts simultaneously. This ability is fundamental for problem solving, creativity, and learning (e.g., Barbey et al., 2013; Boger-Mehall, 1996; Nijstad et al., 2010; Pijeira-Díaz et al., 2018), enabling knowledge workers to generate novel ideas, develop innovative solutions, and effectively navigate complex challenges. Superior decision-making performance, for example, requires the ability to use both controlled and semiautomatic cognitive processes in a flexible manner (Laureiro-Martínez & Brusoni, 2018). Learning is also dependent on cognitive flexibility, which enables individuals to modify their mental scripts and behavioral routines to comply with changing task demands and contextual conditions (Ritter et al., 2012).

Cognitive flexibility is closely tied to the strength of executive control, which enables efficient shifting of attentional and cognitive resources to process new information while disengaging from previously relevant information (Miyake et al., 2000). HRV and stress arousal are two important physiological measures that have been found to be related to self-regulatory capacity and cognitive functions involving executive control (McCraty & Shaffer, 2015). Empirical findings, however, have suggested mixed results. For example, studies conducted in laboratory settings have demonstrated that reduced HRV can impair cognitive flexibility (Colzato et al., 2018; Thayer et al., 2009; for a review and meta-analysis, see Magnon et al., 2022). Increased stress arousal, however, has been linked to both improvements (e.g., Kofman et al., 2006) and impairments in cognitive flexibility (Marko & Riečanský, 2018). The notion that stressful events can have both positive and negative impacts on cognitive performance is an expansion of the inverted U of Yerkes–Dodson law (Yerkes & Dodson, 1908), which posits that performance decreases when arousal levels fall below or surpass an optimal level. Thus, optimal performance can be achieved by maintaining a sufficient level of arousal by avoiding both excessive distress and drowsiness (Diamond et al., 2007). Moderate levels of stress can, for example, increase cognitive performance in learning and problem solving (Pijeira-Díaz et al., 2018) because it increases alertness, focus, and motivation that facilitate better performance (Yerkes & Dodson, 1908). Based on the Yerkes–Dodson law, we predict that higher levels of subjective drowsiness, increased RMSSD, and decreased LF/HF will be associated with impaired cognitive flexibility following meetings.

> *Hypothesis 4:* (a) Increased subjective drowsiness, (b) increased RMSSD, and (c) decreased LF/HF increase cognitive flexibility impairment after meetings.

Linking Hypotheses 1a–c and 2a–c with Hypothesis 4a–c, we propose indirect effects of participating in virtual (vs. face-to-face) meetings on cognitive flexibility impairment via subjective drowsiness, RMSSD, and LF/HF.

> *Hypothesis 5:* (a) Subjective drowsiness, (b) RMSSD, and (c) LF/HF mediate the indirect relationship between virtual (vs. face-to-face) meetings and cognitive flexibility impairment.

Further, our combined Hypotheses 3a–c and 5a–c imply that the strength of the indirect relationships between participation in virtual meetings and impaired cognitive flexibility via passive fatigue (subjective drowsiness and RMSSD) and stress arousal (LF/HF) may differ depending on the level of work engagement. In other words, general work engagement makes employees more or less vulnerable to fatigue in virtual meetings, such that the indirect effects of virtual meetings on cognitive flexibility impairment will be stronger among those with low general work engagement and weaker among the generally highly engaged.

Hypothesis 6: On the meeting level, the indirect effects of participation in virtual meetings on cognitive flexibility impairment via (a) subjective drowsiness, (b) RMSSD, and (c) LF/HF will be stronger among employees with lower levels of general work engagement.

Method

Participants

Fifty knowledge workers from two Finnish multinational corporations participated in the study. The criteria for the participant selection included membership of a virtual team, location in the headquarters (to enable observation on-site), normal general health including a body mass index of 18–30, no substance abuse, no excessive caffeine consumption, no pregnancy or breastfeeding, free of a diagnosed medical condition, and not on any medication that could affect the functioning of the autonomous and/or central nervous system. Consent for the data collection was obtained via company human resources representatives, who recruited voluntary participants for the study. Of the 50 participants, 44 participated in work meetings, from which we could collect data. Five participants were excluded from the study because they did not have any work meetings during the study period. One dropout was due to technical problems with the HRV data. The remaining 44 participants provided 60-hr of continuous HRV measurements during 2 workdays and one night before and after the workdays (i.e., three nights). Thirteen (29.5%) of them were female and 33 (70.5%) were male. Seventeen (38.6%) had a managerial status, whereas 27 (61.4%) worked in expert positions. The mean age of the participants was 38.1 years. At the time of study, they were working on an average of four simultaneous ongoing projects and had worked in their companies for 7.7 years, on average.

Procedure and Measures

The research protocol was reviewed and approved by the Helsinki regional ethical committee (114/13/03/00/13). At the beginning of the study, each participant signed a consent form and filled in a background survey that included questions on demographics (gender, age); typical daily intake of caffeine, alcohol, or cigarettes; the amount of sleep; as well as general work engagement. *General work engagement* was assessed on the short version of the Utrecht Work Engagement Scale (Schaufeli et al., 2006), which consists of nine items with three subscales: vigor (e.g., “At my work, I feel I am bursting with energy”), dedication (e.g., “My job inspires me”), and absorption (e.g., “I am immersed in my work”). Each dimension was assessed on three items, rated on a 7-point scale ranging from 0 (*never*) to 6 (*daily*).

Time-Stamped Field Observations

We collected field observation data by shadowing the informants (one informant at a time) at their offices for a total of 88 days (2 full workdays per informant): This included 382 work meetings (118 virtual and 264 face-to-face). On average, the informants participated in 1.6 observed virtual meetings and three observed face-to-face meetings per day. Virtual meetings lasted on average 46.4 min and face-to-face meetings 25.5 min per each. The average number of other participants in virtual meetings was 4.5 persons and in face-to-face meetings 3.5 persons.

We developed a software tool that enabled us to take field notes and produce observation logs of the participants’ activities during the studied meetings. With this tool, we could precisely time stamp each activity and systematically label them, which allowed us to combine the observation data with the cardiac measurements. The observation logs contained detailed information on all interactions and activities performed by participants during their workdays. Our software was designed to include a list of predefined, commonly observed workplace activities that can be selected during the observation process. Additionally, we could also write detailed open-ended field notes about the activities, the contexts, and other participants in the virtual and face-to-face meetings. To make the fieldwork more efficient, our software features an activity button that we could click when a certain activity began and when it ended. This added time-stamped notes automatically to the observation logs for each activity’s commencement and end. Afterward, we exported the data to Excel, where the activities were coded and calculated in numeric format.

We formed a dichotomous variable “virtual versus face-to-face meeting” on the basis of our field observations. This variable was coded 1 when the meeting was virtual (i.e., online or teleconference) and 0 when it was face-to-face.

Cardiac Measurements of Passive Fatigue (RMSSD) and Active Fatigue (LF/HF)

We used wearable Firstbeat Bodyguard2 devices (First beat Technologies Ltd., Finland) to collect HRV data continuously from each participant during the 2 observed workdays and the related nights before and after each measurement day (60 measurement hr/individual). In a recent comparison of wearable heart rate sensors (Umair et al., 2021), Firstbeat Bodyguard2’s electrocardiography chest strap was found to achieve the highest reliability in measuring HRV with the lowest amount of artifacts compared to other currently available wearable technologies. Firstbeat Bodyguard2 captures the data using two disposable precordial electrodes connected to the skin and the data are accessible via Firstbeat software.

The participants received the devices and user instructions by mail. On the evening before the first studied workday, they attached the device to the skin: one electrode below the right clavicle and the other electrode on the lower left rib cage. Participants were instructed to keep the device in place throughout the whole 60-hr measurement period (2 workdays and three nights), except during showering. They were also instructed to report sleeping times from the three recorded nights in the Firstbeat online diary that was linked with their cardiac data. On the morning after the second study day, they removed the device and mailed it back to the researchers. At the beginning of each observation day, the researcher checked that the device was installed correctly and remained in place throughout the study period.

We measured *passive fatigue* by calculating the root mean square of successive interbeat intervals (RMSSD) and *active fatigue* by calculating the HF power, LF power, and their ratio LF/HF values from the cardiac data (for a meta-analysis and review, see Kim, Cheon, et al., 2018) during the observed meetings. These meetings lasted 5–205 min, and the RMSSD and LF/HF were analyzed from these periods using the Colibri package (Henelius & Korpela, 2014) for R software. The data from each meeting were divided into segments with a length of 5 min and HRV aggregates for each meeting time period were then calculated from the segments. Before generating the RMSSD and LF/HF values for each meeting, we detected and removed artifacts using the method of Xu et al. (2001) and performed a visual inspection of the cleaned data. The Shapiro–Wilk test showed that the HRV measures were not normally distributed. To address this, an ln transformation was performed for better statistical analysis and interpretation as recommended by Massaro and Pecchia (2019).

High levels of RMSSD and low levels of LF/HF indicate low arousal and increased *passive fatigue*, and in contrast, low levels of RMSSD and high levels of LF/HF indicate high-stress arousal and increased *active fatigue* (e.g., Gonzalez et al., 2017; Segerstrom & Nes, 2007; Vicente et al., 2016). Prior research offers insight into the reliability and sensitivity of wearable cardiac measures in studying passive and active fatigue (see Umair et al., 2021).

Subjective Measure of Passive Fatigue (Drowsiness)

After the observed meetings, the informants were asked to fill out a short online survey to rate their *subjective drowsiness* during the meeting with the 10-point KSS (Åkerstedt & Gillberg, 1990), using the following scores: 1 = *extremely alert*, 2 = *very alert*, 3 = *alert*, 4 = *rather alert*, 5 = *neither alert nor sleepy*, 6 = *some signs of sleepiness*, 7 = *sleepy, but no effort to keep awake*, 8 = *sleepy, some effort to keep awake*, 9 = *very sleepy, great effort to keep awake, struggling against sleep*, 10 = *extremely sleepy, falling asleep all the time*.

The KSS has been suggested to correlate with HRV variables (e.g., RMSSD; Schmidt et al., 2017) and used to measure passive fatigue caused by monotony (e.g., Jarosch et al., 2019; Schmidt et al., 2009, 2011). In accordance with these studies, the KSS was used as a subjective measure of passive fatigue in this study.

Cognitive Flexibility Impairment

Following the lines of previous studies (Arbuthnott & Frank, 2000; Spector & Biederman, 1976; Vandierendonck et al., 2010, for a review, see Monsell, 2003), we measured the study participants' cognitive flexibility (or its impairment) by means of a task-switching test 0–30 min after the observed meetings. We used Leinikka et al.'s (2014) validated task-switching paradigm, which is developed to measure mild cognitive impairments or intact cognitive processes among the general population in their natural settings. The test is a modified three-phased version of a Number–Letter task (Pashler, 2000; Vandierendonck et al., 2010), allowing stronger ecological validity of results because it can be taken during the participants' normal daily life. It is notably shorter than other task-switching paradigms, lasting 7–10 min on average. Participants took the task-switching test either at their own desks or in a quiet meeting room using the researcher's computer. At the beginning of the test, they were informed that both speed and accuracy are equally important. They were obliged to briefly practice each of the tasks at least once, but a maximum of 3 times, before the actual test to control for the learning effect.

The Leinikka et al. (2014) test produces an index of *cognitive flexibility impairment* (switch cost) that represents the performance cost of switching between sequential tasks of switch trials, in which participants must shift their attention between distinct cognitive stimulus dimensions, and task repetition trials, in which only one cognitive stimulus dimension is relevant (e.g., Koch et al., 2005; Philipp et al., 2008). In this test, a Letter–Number task is repeated across successive trials in a categorization task, while a task-switching trial requires participants to alternate between Letter–Number and spatial tasks. Cognitive flexibility impairment can arise when participants need to switch between different types of tasks, as this requires them to engage in different cognitive processes and shift attention from the previous stimuli to a new stimulus (Posner, 1980).

The Leinikka et al. (2014) test comprises three tasks: a detection task, measuring baseline reaction time; a categorization task, measuring categorization ability; and a switching task, measuring the switch cost. In all tasks, letter–number pairs (e.g., a7) are displayed either above or below a fixed horizontal line to the participant, and a horizontal jitter is used to minimize the chance of the participants fixating on a certain spot. The responses are given by pressing either the X or M key from the keyboard. At the conclusion of each of the three tasks, the participant received feedback on the percentage and the average response time for correct answers.

In the first task, detection task, a baseline reaction time is measured by asking the participant to press the key X as fast as possible when they notice a specific stimulus on the screen. This detection task phase consists of 10 trials. The letter–number pairs are viewable until the subject gives their response, but there is an upper limit of reaction time of 1950 ms. Button presses between 40 and 1950 ms poststimulus onset are regarded as responses. To discount probable mishits, the reaction times that are less than 39 ms are disregarded from the records (Leinikka et al., 2014).

The second task, categorization task, comprises 80 trials, and it measures categorization ability. First, letter–number pairs are displayed above the horizontal line, and the goal is to identify the pair's number as either odd or even by pushing X or M on the keyboard. Same stimulus pairs are then placed underneath the horizontal line, and the task is to classify the pair's letter whether it is consonant or vowel by pressing X or M. Because the pairs of letters and numbers are semirandom, each letter and number occur the same amount in all possible combinations. The trials consist of the first 40 above the line and 40 below the line (Leinikka et al., 2014).

In the final task, switching task, the participants perform both the above-described categorization tasks alternately. This time, the letter–number pairs are displayed above or below the horizontal line, by turns. The task varies depending on the location cue. For example, if the letter–number pair is shown above the horizontal line, the task is to identify the pair's numbers as odd or even. When the pair is shown below the horizontal line, the task is to identify the pair's letter as consonant or vowel, by either pressing X or M (Leinikka et al., 2014). Our dependent variable, *cognitive flexibility impairment*, was calculated as switch cost in terms of the difference in error rate between the two trial modes (switch trials and repeat trials) within the switching task block.

The source code, hosting instructions, and an online version of the Leinikka et al. (2014) task-switching test are available at http://github.com/measureself/cognitive-flexibility.

Control Variables

Prior literature in meeting science suggests that several meeting characteristics can affect attendee fatigue (see Allen & Lehmann-Willenbrock, 2022, for a review). Therefore, we controlled for perceived meeting-specific demands, including mental, physical, and temporal demands, as well as the effort put into executing tasks during the meeting. To measure these meeting-level control variables immediately after each meeting, participants were asked to fill out a modified version of the The National Aeronautics and Space Administration-Task Load Index questionnaire (Hart & Staveland, 1988) focusing on the meeting in which they just participated. *Mental demand* was measured by asking: "How much mental and perceptual activity was required during the meeting?" *Physical demand* was measured by asking: "How physically demanding was the meeting?" To measure *temporal demand*, we asked: "How hurried or rushed was the pace of the meeting?" For measuring *effort*, we asked: "How hard did you have to work to accomplish your level of performance in the meeting?" The participants rated for each attended meeting on a 100-point scale (0 = *no demands*, 100 = *very high demands*).

Based on our field notes, we also formed other meeting-level control variables that could potentially influence meeting attendees' fatigue. Previous research from the field of meeting science suggests that objective meeting characteristics, such as technical problems (Nesher Shoshan & Wehrt, 2022), meeting size (Allen et al., 2020; Cohen et al., 2011), and duration (Romano & Nunamaker, 2001), may influence attendee experiences and attitudes toward the meeting. Therefore, we incorporated five control variables of objective meeting characteristics: "technical problems," that is, observed technical obstacles or hassles that hindered the progress of the meeting, "meeting size," that is, the number of participants in the observed meeting, and "meeting duration" measured in minutes. Prior research also links a higher number of meetings to increased fatigue and workload (Luong & Rogelberg, 2005). As such, we included a control variable, "meeting number," derived from the observational data. This variable reflects the ordinal position of the observed meeting in an individual's daily schedule, counting the number of prior meetings the individual had attended on the same day. We also controlled for "time of day." We coded this variable as 0 for meetings that occurred before 9 a.m.; 1 for morning meetings occurring between 9:00 a.m. and 11:59 a.m.; 2 for afternoon meetings held between 12:00 p.m. and 4:59 p.m.; and 3 for meetings that started at 5:00 p.m. or later.

Finally, we added three individual-level control variables. Although HRV parameters, RMSSD and LF/HF, have been found to fluctuate in response to different work demands (e.g., Parker et al., 2020; Uusitalo et al., 2011), they also exhibit significant interindividual differences (Thayer et al., 2012). Therefore, to control for individual demographic differences, we controlled for *gender*, *age*, and baseline RMSSD, calculating individual-level baseline value "sleep time RMSSD" by aggregating the sleep time RMSSD segments from the sleeping times that the participants reported in their Firstbeat online diaries.

Analytical Approach

Accounting for the hierarchical structure of our data (i.e., meeting-level data nested in individuals), we used multilevel structural equation modeling (SEM) with maximum likelihood estimation and Stata software Version 18.0 to test our hypotheses. We followed the recommendations of Preacher et al. (2010) and specified one overall multilevel model, including a within-person (meeting-level, Level 1) and a between-person (individual-level, Level 2) estimations. Accordingly, we calculated the associations between the meeting-level independent variable (virtual meeting) and the dependent variable (cognitive flexibility impairment) via all the proposed mediator variables (subjective drowsiness, RMSSD, and LF/HF) simultaneously, which allowed for the examination of the effects of each mediator while controlling for the others. To test the role of individual-level moderator (general work engagement) and the moderated mediation effects of subjective drowsiness, RMSSD, and LF/HF, we tested the multilevel SEM (Figure 1) with one mediator at a time, as recommended by Preacher et al. (2007).

Results

Preliminary Analysis

Table 1 presents the means, standard deviations, intraclass correlations, and bivariate correlations of the study variables. Virtual versus face-to-face meeting participation was positively and significantly related to RMSSD ($r = 0.15$, $p < .001$), LF/HF ($r = -0.16$, $p < .001$), and impaired cognitive flexibility ($r = 0.11$, $p < .05$), but not to subjective drowsiness ($r = 0.09$, $p = .10$, *n.s.*) on the meeting level. The mediators, that is, subjective drowsiness ($r = 0.52$, $p < .001$), RMSSD ($r = 0.25$, $p < .001$), and LF/HF ($r = -0.05$, $p < .05$), were significantly related to the dependent variable (cognitive flexibility impairment). We also ran analysis of variance analyses to see whether virtual meetings differed from face-to-face meetings on any of the study's variables (see Table 2). Results showed that virtual meetings, as compared with face-to-face meetings, were more likely to be experienced physically and temporally more demanding, include more technical problems, involve more participants, and last longer. According to the intraclass correlations of the meeting-level variables, within-person fluctuations explained a significant amount of the variance in the mediators and the outcome variable: 31% for subjective drowsiness, 75% for RMSSD, 67% for LF/HF, and 63% for cognitive flexibility. It thus seems that multilevel modeling is appropriate for testing the hypotheses.

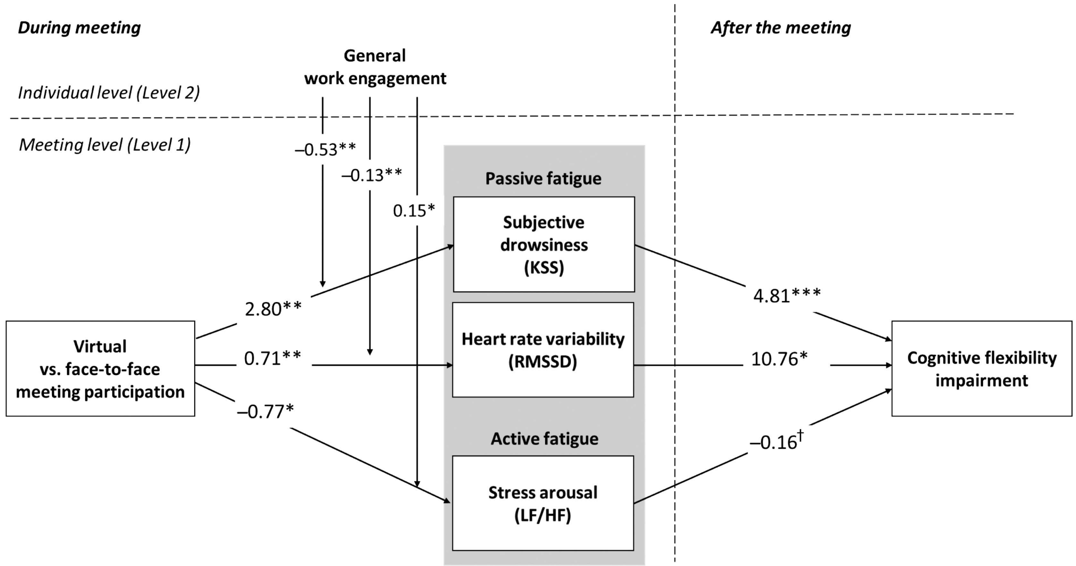
Hypothesis Testing

Figure 1 and Table 3 present the results from the multilevel SEM analysis that estimated all the path coefficients simultaneously. This multilevel moderated mediation model consisted of 15 meeting-level (Level 1) variables (virtual vs. face-to-face meeting participation, subjective drowsiness, RMSSD, LF/HF, cognitive flexibility impairment, the interaction term, and nine control variables related to meeting characteristics), as well as four individual-level (Level 2) variables (work engagement, gender, age, and sleep-time RMSSD). This 19-factor model fits the data better (Akaike information criterion [AIC] = 2432.19, Bayes information criterion [BIC] = 2700.63) than theoretically plausible alternative models, that is, a multilevel model consisting of the main effects of predictors but no interaction effect (AIC = 2440.70, BIC = 2697.63), or a multilevel model consisting of only the control variables (AIC = 2536.91, BIC = 2778.50). Lower values on AIC and BIC indicate better fitting models (Masyn, 2013).

Our results show that participation in virtual (vs. face-to-face) meetings was significantly and positively related to subjective drowsiness ($B = 2.80$, $p < .01$) with a 95% confidence interval (CI) from 0.18 to 4.80. Because the CI did not include zero, the effect was significant. Participation in virtual meetings was also significantly

Figure 1

The Effects of Virtual (vs. Face-to-Face) Meetings on Passive Fatigue, Active Fatigue, and Cognitive Performance



Note. Unstandardized coefficients of the estimated model. This figure does not include the following for reasons of brevity: the effects of the control variables and the main effects of the individual-level moderator on the meeting-level mediating variables. For these estimates, see Table 3.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

related to RMSSD ($B = 0.71$, $p < .01$; CI [0.23, 1.19]) and LF/HF ($B = -0.77$, $p < .05$; CI [−1.50, −0.04]), thereby supporting the passive fatigue hypotheses (H1a–c) and not the active fatigue hypotheses (H2a–c). These findings suggest that virtual meeting fatigue may be more related to passive fatigue than active fatigue.

As hypothesized in H3a–c, work engagement moderated the effects of virtual meetings on subjective drowsiness ($B = -0.53$, $p < .01$; CI [−0.93, −0.14]), RMSSD ($B = -0.13$, $p < .01$; CI [−0.23, −0.04]), and LF/HF ($B = 0.15$, $p < .05$; CI [0.03, 0.29]). To determine the specific forms of these interactions, we conducted simple slope analyses in multilevel modeling (Preacher et al., 2007). Table 4 and the plots shown in Figures 2–4 illustrate that employees with lower levels of general work engagement (−1 *SD*, $n = 13$) were more likely to report higher subjective drowsiness ($B = 1.11$, $p < .01$), higher HRV (RMSSD; $B = 0.18$, $p < .01$), and lower stress arousal (LF/HF; $B = -0.36$, $p < .001$) in virtual meetings compared to face-to-face meetings. On the other hand, employees whose work engagement level was at the mean level ($n = 17$) did not exhibit significant differences in these measures between the two meeting types ($B = 0.29$, $p = .24$, *n.s.*; $B = 0.07$, $p = .13$, *n.s.*; $B = -0.07$, $p = .28$, *n.s.*, respectively). At the higher levels of work engagement (+1 *SD*, $n = 14$), virtual meeting participation was not related to subjective drowsiness ($B = -0.03$, $p = .90$, *n.s.*), but the relationship was significant for RMSSD ($B = 0.10$, $p < .05$) and LF/HF ($B = -0.13$, $p < .05$). These findings suggest that employees with lower intrinsic motivational draw to their work may *perceive* virtual meetings more tiring than those who are generally more excited about and engaged in their work. However, it is important to note that virtual meeting participation can still result in passive fatigue, as evidenced by an increase in HRV (RMSSD) and a decrease in stress arousal (LF/HF), for both highly engaged employees and those with lower levels of engagement. In other words, while lower work engagement is associated with *perceiving* virtual meetings as more tiring, virtual meetings can still impact physiological fatigue indicators among employees with different engagement levels.

Hypothesis 4 was supported in that subjective drowsiness ($B = 4.81$, $p < .001$; CI [3.02, 6.60]), RMSSD ($B = 10.76$, $p < .05$; CI [0.81, 20.71]), and LF/HF ($B = -0.16$, $p = .09$; CI [−35.01, −2.72]) were all positively related to impaired cognitive flexibility. Monte Carlo confidence intervals were calculated to test the indirect effects. The indirect effect of virtual meeting participation and postmeeting cognitive flexibility impairment via subjective drowsiness was 8.87 ($p < .05$) with a 95% bias-correlated bootstrap CI from 1.19 to 17.83. Virtual meetings also had a significant indirect effect on cognitive flexibility impairment via RMSSD: 5.38 ($p < .05$; CI [1.80, 10.20]), but not via LF/HF: 2.43 ($p = .14$; CI [−0.43, 6.20]). Thus, Hypotheses 5a and b were supported, but Hypothesis 5c was not.

Finally, in Hypothesis 6a–c, we tested the extent to which the estimated indirect effects of virtual (vs. face-to-face) meetings on cognitive flexibility via subjective drowsiness, RMSSD, and LF/HF differed on the lower (−1 *SD*), medium (mean), and higher (+1 *SD*) levels of general work engagement. Although we did not find direct effects between virtual meeting participation and cognitive flexibility, recent research suggests that this condition is not required for mediation (e.g., Preacher & Hayes, 2004). Instead, we focused on evaluating the indirect effects to assess the mediating role of subjective drowsiness, RMSSD, and LF/HF. First, at the low level of work engagement, subjective drowsiness and RMSSD were significantly related to cognitive flexibility impairment ($B = 3.13$, $p < .01$; CI [0.92, 5.33]; $B = 98{,}06$, $p < .001$; CI [46.47, 149.65], respectively), but LF/HF was not ($B = -22.63$, $p = .17$, *n.s.*; CI [−55.18, 9.91]). At the medium level of work engagement, only

Table 1

Means, Standard Deviations, and Correlations of the Study Variables

Variable	*M*	*SD*	ICC	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Virtual versus face-to-face meeting[a]	0.31	0.46	.19	—	.182	.230	−.189	.224	−.015	.192	.482**	.025	.341*	.316*	.509**	−.850	−.213	−.130	.038	.143	.328*
2. Subjective drowsiness (KSS)	3.08	1.34	.31	.085	—	.330*	−.281	.344*	.054	.245	.261	.050	.051	.180	.334*	.029	.118	−.129	.040	.181	.069
3. Heart rate variability (lnRMSSD)	3.52	0.44	.75	.151**	.222**	—	−.725**	.347*	−.245	.049	.086	−.178	−.065	.290	.157	−.029	−.027	.015	−.058	.672**	.113
4. Heart rate variability (lnLF/HF)	1.48	0.59	.67	−.164**	−.132*	−.694**	—	−.107	.068	−.189	−.269	−.070	−.147	−.101	−.289	.004	−.075	.338*	−.162	−.412**	−.135
5. Cognitive flexibility impairment	37.72	14.77	.63	.108*	.517**	.252**	−.052*	—	−.263	−.214	−.087	−.105	−.077	.340*	.249	−.108	−.095	.056	.185	.213	.110
6. Mental demands	49.83	26.21	.15	−.054	−.051	−.278**	.106*	−.111	—	.267	.164	.582**	.207	−.350*	.127	−.039	−.033	.046	−.145	−.177	−.061
7. Physical demands	7.55	13.23	.16	.152**	.155**	.012	−.100	−.088	.305**	—	.284	.205	.247	.183	.250	−.094	−.102	.029	−.194	.044	−.182
8. Temporal demands	34.63	25.57	.20	.336**	.072	.126*	−.163**	−.151	.006	.250**	—	.094	.349*	.173	.629**	.120	.027	−.274	−.035	.056	.074
9. Effort demands	43.39	22.44	.11	−.069	−.085	−.217**	.003	−.086	.637**	.252**	−.056	—	.308*	.101	.161	−.058	.346*	−.201	.093	−.127	.011
10. Technical problems	0.12	0.33	.24	.454**	.017	.039	−.095	−.068	.039	.149**	.214**	.007	—	.059	.336*	.050	−.014	−.136	.079	.072	−.052
11. Meeting size	3.80	2.98	.04	.160**	.212**	.160**	−.128*	.155	−.124*	.058	.198**	−.032	.098	—	.278	−.060	.072	.070	.039	.246	−.073
12. Meeting duration	31.97	29.84	.05	.325**	.154**	.150**	−.206**	.032	−.072	.253**	.365**	−.103*	.215**	.373**	—	−.072	−.280	−.205	.111		.028
13. Meeting number	3.45	2.35	.16	.058	−.006	.077	−.014	−.066	−.125*	−.075	−.031	−.107*	−.030	−0.035	−.073	—	.239	.249	.015	−.027	.261
14. Time of day	1.48	0.65	.03	.059	.028	.035	−.053	.010	−.047	−.074	−.094	.055	−.061	.009	−.046	.584**	—	−.287	.037	−.053	.173
15. Gender[b]	0.64	0.48		−.101*	−.052	−.017	.323**	.123	.010	−.010	−.113*	−.126*	−.062	.008	−.088	.189**	−.077	—	−.034	.155	.097
16. Age	38.16	6.33		.006	−.026	−.141**	−.087	.117	−.025	−.078	−.004	.065	.014	−.017	.021	−.032	.002	−.086	—	−.238	.362*
17. Sleep time RMSSD (baseline)	52.30	24.08		.046	.124*	.631**	−.406**	.147	−.062	.023	.066	−.016	.049	.113*	.056	.037	.013	.073	−.298**	—	−.219
18. General work engagement	4.71	0.82		.173**	−.013	.071	−.046	.175*	−.081	−.121*	.020	−.047	−.056	−.014	−.014	.181**	.068	.155**	.297**	−.180**	—

Note. Correlations above the diagonal depict individual-level correlations (N = 44). Individual-level correlations of meeting-level variables are based on the individual mean. Correlations below the diagonal depict meeting-level correlations (N = 382). ICC = intraclass correlation; KSS = Karolinska Sleepiness Scale; RMSSD = root-mean-squared standard deviation; HF = high frequency; LF = low frequency.

[a] 0 = face-to-face, 1 = virtual meeting. [b] 0 = female, 1 = male.

$^{*}p < .05$. $^{**}p < .01$.

Table 2
ANOVA Analysis Results Comparing Virtual and Face-to-Face Meetings

Variable	Virtual meetings (N = 118)	Face-to-face meetings (N = 264)	Univariate F
Demographics			
Gender (female = 0, male = 1)	0.63	0.73	3.89*
Age (mean age in years)	38.19	38.11	0.02
Meeting characteristics			
Mental demands (on the scale of 0–100)	47.70	50.78	1.12
Physical demands (on the scale of 0–100)	10.55	6.21	8.95**
Temporal demands (on the scale of 0–100)	47.47	28.89	48.40***
Effort demands (on the scale of 0–100)	41.08	44.42	1.81
Technical problems (no. of observed problems in the meeting)	0.37	0.03	88.29***
Meeting size (no. of participants in the meeting)	4.52	3.48	10.03**
Meeting duration (min)	46.44	25.5	44.78***
Meeting number (ordinal number of the meeting in the day)	3.65	3.36	1.30
Time of day (1 = before 9 a.m., 2 = between 9 a.m. and noon, 3 = between noon and 4 p.m., 4 = after 5 p.m.)	1.53	1.45	1.33

Note. ANOVA = analysis of variance.
* $p < .05$. ** $p < .01$. *** $p < .001$.

subjective drowsiness had a significant relationship with cognitive flexibility impairment ($B = 2.21$, $p < .01$; CI [0.32, 4.10]), while RMSSD and LF/HF did not ($B = -7.31$, $p = 0.83$, *n.s.*, CI [−76.04, 34.91]; $B = -0.03$, $p = 0.99$, *n.s.*, CI [−44.01, 43.96]; respectively). At the higher level of work engagement, subjective drowsiness and RMSSD were significantly related to cognitive flexibility impairment ($B = 4.92$, $p < .001$, CI [2.16, 7.68]; $B = 53.27$, $p < .05$, CI [5.23, 101.31]), whereas LF/HF did not show a significant relationship ($B = -21.39$, $p = .19$, *n.s.*, CI [−53.49, 10.71]). Supporting Hypothesis 6a, the indirect effect of virtual meeting participation on cognitive flexibility impairment via subjective drowsiness was significant only at the low work engagement level: 3.48 ($p < .05$; CI [0.71, 7.53]), but not at the medium level: 0.64 ($p = .32$, *n.s.*; CI [−0.44, 2.16]) or higher level: −0.15 ($p = .91$, *n.s.*; CI [−2.72, 2.38]). Supporting Hypothesis 6b, virtual meetings also exhibited a significant indirect effect on cognitive flexibility

Table 3
The Results of the Multilevel Structural Equation Model Analysis

Variable	M: Subjective drowsiness (KSS)	M: Heart rate variability (RMSSD)	M: Stress arousal (LF/HF)	DV: Cognitive flexibility impairment
Meeting-level independent variable				
Virtual versus face-to-face meeting	2.80**	0.71**	−0.77*	1.38
Meeting-level control variables				
Mental demands	0.00	−0.01**	0.00	−0.05
Physical demands	0.02**	0.01*	−0.01**	−0.01
Temporal demands	−0.00	−0.01	−0.00	−0.06
Effort demands	−0.01*	−0.01**	0.00	−0.00
Technical problems	−0.24	−0.05	−0.01	1.51
Meeting size	0.10***	0.01	−0.01	−0.07
Meeting duration	−0.00	0.00	−0.00	0.01
Meeting number	−0.01	0.01	−0.00	−0.68
Time of day	0.11	0.00	−0.02	2.58
Individual-level control variables				
Gender	−0.16	−0.13**	0.49***	1.78
Age	0.00	0.00	−0.02***	0.41*
Sleep time RMSSD (baseline)	0.01**	0.01***	−0.01***	0.00
Individual-level moderator				
Work engagement	0.11	0.15***	−0.15***	1.16
Meeting-level interaction term				
Virtual Meeting × Work Engagement	−0.53**	−0.13**	0.15*	
Meeting-level mediators (M)				
Subjective drowsiness (KSS)				4.81***
Heart rate variability (RMSSD)				10.76*
Stress arousal (LF/HF)				−0.16†

Note. Unstandardized restricted maximum likelihood estimates predicting meeting-level mediators (M) and the dependent variable (DV), (N = 382). KSS = Karolinska Sleepiness Scale; RMSSD = root-mean-squared standard deviation; HF = high frequency; LF = low frequency.
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 4

The Indirect Effects of Virtual Meetings on the Outcome Variables at Lower, Medium, and Higher Levels of General Work Engagement

	Bootstrapping		PC 95% CI	
Hypothesis/path	Estimate	*SE*	*LL*	*UL*
Direct effects $x \rightarrow m$				
H3(a) Virtual meeting → subjective mental fatigue (KSS)				
At a high level of work engagement (+1 *SD*)	−0.03	0.24	−0.51	0.45
At a medium level of work engagement (*M*)	0.29	0.24	−0.20	0.78
At a low level of work engagement (−1 *SD*)	**1.11****	**0.37**	**0.37**	**1.86**
H3(b) Virtual meeting → heart rate variability (RMSSD)				
At a high level of work engagement (+1 *SD*)	**0.10***	**0.04**	**0.02**	**0.19**
At a medium level of work engagement (*M*)	0.07	0.04	−0.02	0.15
At a low level of work engagement (−1 *SD*)	**0.18****	**0.06**	**0.06**	**0.30**
H3(c) Virtual meeting → stress arousal (LF/HF)				
At a high level of work engagement (+1 *SD*)	**−0.13***	**0.06**	**−0.25**	**−0.00**
At a medium level of work engagement (*M*)	−0.07	0.07	−0.21	0.06
At a low level of work engagement (−1 *SD*)	**−0.36*****	**0.10**	**−0.56**	**−0.16**
Indirect effects $x \rightarrow m \rightarrow y$				
H6(a) Virtual meeting → subjective fatigue (KSS) → cognitive flexibility impairment				
At a high level of work engagement (+1 *SD*)	−0.15	1.24	−2.72	2.38
At a medium level of work engagement (*M*)	0.64	0.65	−0.44	2.16
At a low level of work engagement (−1 *SD*)	**3.48***	**1.71**	**0.71**	**7.53**
H6(b) Virtual meeting → heart rate variability (RMSSD) → cognitive flexibility impairment				
At a high level of work engagement (+1 *SD*)	5.33	3.43	−0.21	13.31
At a medium level of work engagement (*M*)	−0.49	2.79	−6.78	5.33
At a low level of work engagement (−1 *SD*)	**17.55***	**7.72**	**4.65**	**34.91**
H6(c) Virtual meeting → stress arousal (LF/HF) → cognitive flexibility impairment				
At a high level of work engagement (+1 *SD*)	2.67	2.60	−1.47	8.99
At a medium level of work engagement (*M*)	0.00	2.24	−4.95	4.91
At a low level of work engagement (−1 *SD*)	8.09	6.52	−3.48	22.89

Note. KSS = Karolinska Sleepiness Scale; RMSSD = root-mean-squared standard deviation; HF = high frequency; LF = low frequency; CI = confidence interval; *LL* = lower limit; *UL* = upper limit; H = hypothesis; *SE* = standard error. Bold formatting indicates significant paths.
* $p < .05$. ** $p < .01$. *** $p < .001$.

impairment via RMSSD at the low work engagement level: 17.55 ($p < .05$; CI [4.65, 34.91]), but not at the mean level: −0.49 ($p = .86$, *n.s.*; CI [−6.78, 5.33]) and the higher level: 5.33 ($p = .12$, *n.s.*; CI [−0.21, 13.31]). Hypothesis 6c was not supported, as the indirect effect of virtual meetings on cognitive flexibility impairment via LF/HF was not significant at any level of general work engagement: lower work engagement level: 8.09 ($p = .21$, *n.s.*; CI [−3.48, 22.89]), medium level: 0.00 ($p = .99$, *n.s.*; CI [−4.95, 4.91]), or higher level: 2.67 ($p = .23$, *n.s.*; CI [−1.47, 8.99]). We found no significant direct path between virtual meeting participation and the outcome variable, indicating that subjective drowsiness and passive fatigue serve as mechanisms that transmit the negative effects of virtual meetings on cognitive flexibility, particularly at a low level of work engagement.

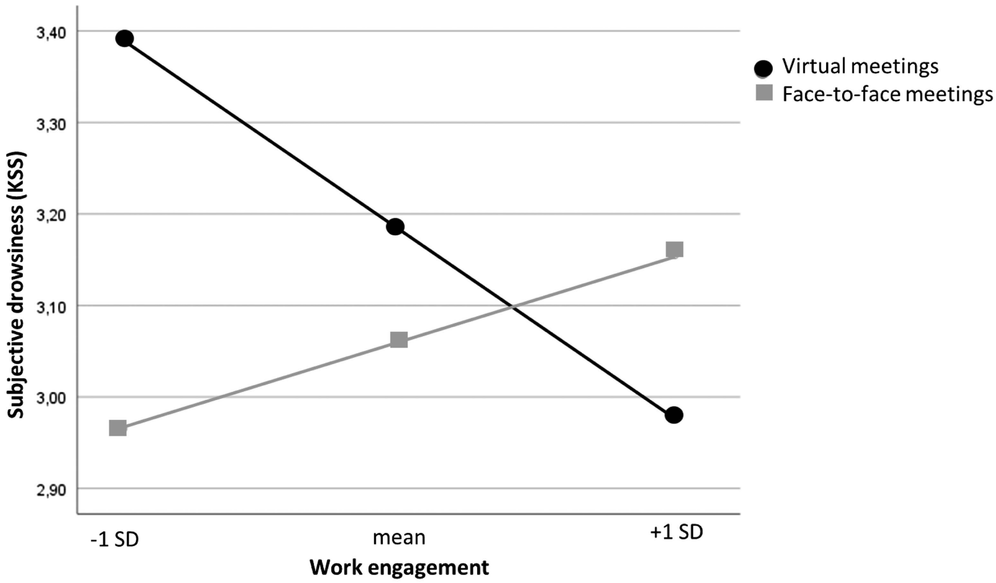
Discussion

This field study explored the psychophysiological process of how participation in virtual (vs. face-to-face) meetings affects passive versus active fatigue and cognitive performance among knowledge workers. Our findings, based on subjective and cardiac measures, suggest that participants experience more passive than active fatigue in virtual meetings, whereas face-to-face meetings did not result in either type of fatigue. Instead, the participants were able to maintain moderate so-called "optimal" levels of stress arousal in most face-to-face meetings, which led to better cognitive flexibility after these meetings. Work engagement was found to be a potential individual-level moderator, which explains why some but not all knowledge workers perceive virtual meetings as more tiring than face-to-face meetings. Our results also indicate that an increase in passive fatigue could detrimentally influence cognitive performance, implying that virtual meetings might have more adverse performance effects compared to face-to-face meetings. Our study demonstrates that wearable HRV detectors can provide new methodological opportunities for organizational research to study psychophysiological processes that influence an individual's affective, motivational, and cognitive processes relevant to organizational settings.

Theoretical Contributions

Our study contributes to the meeting science literature by providing a more nuanced understanding of virtual meeting fatigue. Our findings on passive fatigue contrast prior studies on virtual meeting fatigue that has, so far, focused mostly on the active type of fatigue and related constructs, such as experienced exhaustion (e.g., Bennett et al., 2021; Fauville et al., 2021a; Shockley et al., 2021), perceived stress (e.g., Pennington et al., 2022), and anxiety (e.g., Shahrvini et al., 2021; Vandenberg & Magnuson, 2021). Desmond

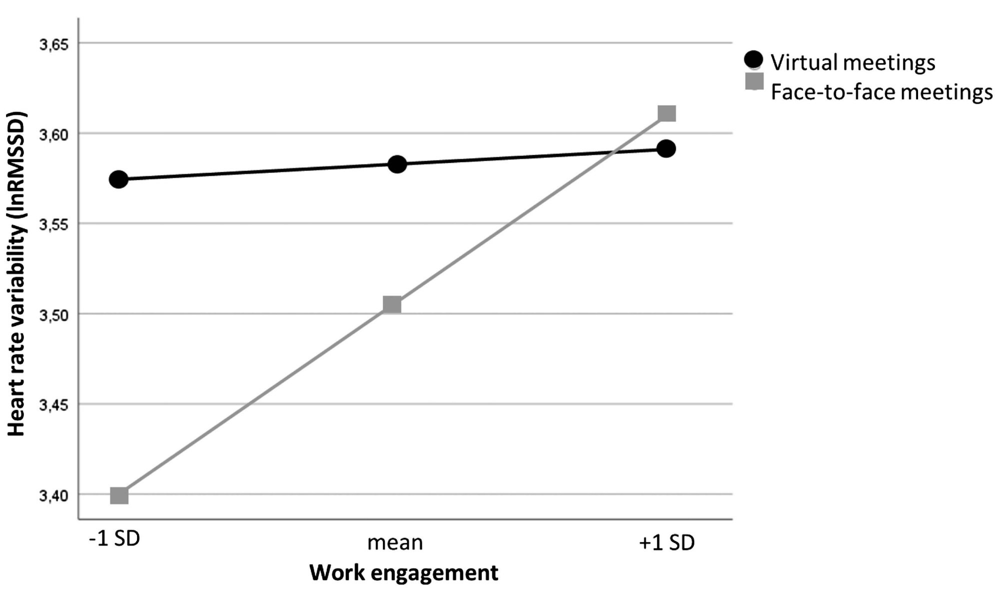
Figure 2
Interaction Between Virtual (vs. Face-to-Face Meetings) and General Work Engagement Predicting Subjective Drowsiness (KSS)



Note. KSS = Karolinska Sleepiness Scale.

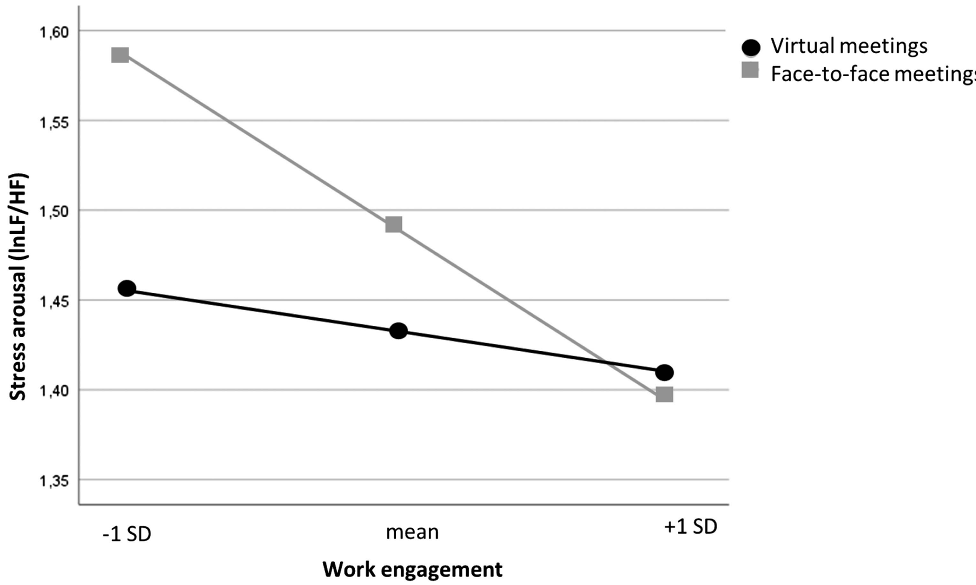
and Hancock's (2001) theory of cognitive fatigue provided us with a useful theoretical lens to investigate different types of fatigue that may occur during meetings because it explains how overload and underload conditions may lead to active and passive fatigue, respectively, requiring different countermeasures. While the previous research on active fatigue has recommended minimizing distracting stimuli, decreasing webcam usage, or hiding self-view during meetings to avoid cognitive overload and exhaustion (e.g., Fosslien & Duffy, 2020), these strategies may not be effective in combating passive fatigue. On the contrary, low stimuli can exacerbate passive

Figure 3
Interaction Between Virtual (vs. Face-to-Face Meetings) and General Work Engagement Predicting Heart Rate Variability (lnRMSSD)



Note. RMSSD = root-mean-squared standard deviation.

Figure 4
Interaction Between Virtual (vs. Face-to-Face Meetings) and General Work Engagement Predicting Stress Arousal (lnLF/HF)



Note. HF = high frequency; LF = low frequency.

fatigue during virtual meetings. Establishing that fatigue is a two-dimensional state resulting from either overload or underload conditions can help to clarify the causes, state, and effects of fatigue in workplaces. For example, by identifying whether fatigue is a result of overload or underload, we can then describe the resulting state of fatigue (active or passive) more specifically to better understand and manage its effects on employees.

Moreover, our study highlights the crucial role of general work engagement as a boundary condition for passive fatigue in virtual meetings. Specifically, employees with lower level of general work engagement reported significantly higher sleepiness and tiredness in virtual compared to face-to-face meetings. Conversely, those with higher levels of work engagement perceived themselves as more vigilant in both meeting formats. These findings align with attention restoration theory (Kaplan, 1995), which suggests that passive fatigue arises when one needs to focus on a task with little or no intrinsically motivational draw. Fascinating tasks, in contrast, may draw effortless attention that does not require cognitive effort and thus does not lead to fatigue (Kaplan & Berman, 2010). Interestingly, however, although lower work engagement was associated with perceiving virtual (vs. face-to-face) meetings as more tiring, our physiological indicators of passive fatigue (increased RMSSD and decreased LF/HF) indicated that virtual meetings can impact employees across different levels of work engagement.

These results provide further research-based evidence for virtual meeting fatigue, highlighting that the modality of virtual meetings, and not any meeting, predicts passive fatigue. Additionally, we found that larger meeting size may increase subjective perceptions of drowsiness in both virtual and face-to-face meetings. Although previous research in meeting science has reported associations between objective meeting characteristics and attendee attitudes toward the meetings (e.g., Allen et al., 2020; Cohen et al., 2011), we did not find significant relationships between physiological fatigue indicators and objective meeting characteristics such as technical problems, meeting size, duration, number, or time of day. Although surprising, these results align with other "zoom fatigue" studies conducted during the COVID-19 pandemic, including the inconclusive findings of Bennett et al. (2021) regarding the objective characteristics of virtual meetings. To address this ambiguity, we explored attendees' subjective experiences of meeting-related demands and found that perceived mental, physical, and effort demands were related to subjective and physiological fatigue. Specifically, increased mental demands and effort were associated with a decrease in passive fatigue, that is, HRV (RMSSD). Intriguingly, heightened physical demands were linked to a decrease in stress arousal (LF/HF), as well as an increase in RMSSD and subjective drowsiness, which may be attributed to the demand for prolonged physical stillness during meetings. Given that research on meetings has rarely crossed paths with physiological perspectives, our study begins to bridge the gap between subjective and physiological research approaches in organizational research.

Our study also contributes to the literature on workplace fatigue by demonstrating the use of wearable cardiac measures to record passive fatigue and stress arousal in field settings. These new methodological tools enable continuous measurements of moment-to-moment psychophysiological responses throughout multiple days. Combined with field observations, continuous cardiac measures allow for a dynamic analysis of how employees react in different situations and how their reactions may influence behavior and performance in organizations. Physiological measures offer insights that can be beyond the scope of self-reports and behavioral observation, particularly those that are typically subject to social desirability concerns (Akinola et al., 2019; Blascovich & Mendes, 2010). Earlier studies that have applied physiological measures in organizational settings and compared them with self-report measures demonstrate that physiological responses may reliably capture stress reactions (Pakarinen et al., 2018) and predict individual behavior (Akinola, 2010; Josephs et al., 2006). Our results extend this work by suggesting that combining cardiac measures with field observations and subjective measures may help detect employee reactions to different job demands (e.g., virtual meetings) and their performance. As a result, our methodological approach increases the precision in the theorizing of relationships between job demands, different types of fatigue, and cognitive performance.

Limitations and Future Research Directions

We should acknowledge a few limitations that offer avenues for future research. In order to minimize measurement error, we used a sample of meetings in which the informants were sitting consistently and not standing, moving, eating, or drinking coffee because such activities may affect HRV. We also excluded those participants with health conditions and on medication that might have affected their autonomic nervous and particularly cardiovascular systems. Therefore, our data sample is limited to a selection of participants with good general health and to interaction events that represent only a narrow range of work situations. Having a small sample size and limited participant selection from only two companies can also have implications for the generalizability of our research findings. With a small sample size, the statistical power of the study may also be limited. This means that the ability to detect significant effects or relationships accurately may be compromised and the findings may be less reliable or have a higher chance of producing Type II errors. Future research should address these limitations by collecting larger samples from various organizations and industries and individuals with diverse demographic characteristics in order to statistically control for variation in organizational factors, individual health, as well as physical and nutritional habits. Moreover, evaluating cognition by means of a separate online test that has to be administered during the working day may seem cumbersome, and sometimes even unmotivating, particularly if the participant's work schedule is tight. There is also a need for future research aimed at measuring cognitive performance based on a carefully designed and controlled work task rather than a task-switching test.

One clear challenge in the use of cardiac measures in organizational research is the question of how to interpret contradictory data from different sources, for example, HRV, self-report, and behavioral data. In our study, for example, highly and moderately engaged employees' self-reports indicated no differences in passive fatigue (drowsiness) experiences during virtual and face-to-face meetings ($B = -0.03$, $p = .09$, *n.s.*; $B = 0.29$, $p = .24$, *n.s.*; respectively) while highly engaged employees' RMSSD revealed higher passive fatigue ($B = 0.10$, $p < .05$) and lower stress arousal LF/HF ($B = -0.13$, $p < .05$) in virtual compared to face-to-face meetings. For the participants with low work engagement, subjective and cardiac measurements of passive fatigue were more balanced. This divergence in self-report and objective data among highly engaged employees calls for future exploration of general work engagement and self-awareness. For example, are highly engaged workers more prone to ignore their negative feelings (like drowsiness) at work as they, in general, perceive their job as stimulating and meaningful, or are they less sensitive to passive fatigue and cognitive performance decrements than those with lower work engagement?

Practical Contributions

In terms of practical contributions, our study highlights the potential costs of virtual meetings of which organizations need to be cognizant as they accelerate their implementation of virtual work. It is clearly not in the interest of any organization to push for more virtual meetings if they come at the cost of employee well-being and cognitive performance. Our findings indicate that a high number of meetings, particularly virtual ones, may drain employees' energies during the working day. Thus, managers should encourage employees to limit the number of meetings to those that are strictly necessary and to prioritize face-to-face meetings when possible. The features of face-to-face meetings, such as synchronicity, flexible conversational flow, and rich social and nonverbal cues, may enable participants to stay engaged and more energetic compared to virtual meetings. We also found that meeting participants experienced less passive fatigue and more "optimal" arousal when the mental and effort demands were higher. Thus, having fewer and more meaningful meetings, with an appropriate task load, could make virtual interactions less tiring.

We also recommend the development of general work engagement that could help employees to manage the demands of virtuality in the increasingly digitalizing world of work. Managers can help boost work engagement among employees, particularly in the context of virtual work, by providing clear expectations, goals, and objectives to employees, and giving employees a sense of ownership and control over their work (Hill et al., 2022). Implementing virtual recognition programs, such as virtual awards or public acknowledgments, to celebrate employees' accomplishments and contributions could also help increase general work engagement among virtual team members. Earlier literature also advises managers to provide virtual team members with learning opportunities; job complexity (Nurmi & Hinds, 2016); and opportunities to connect with each other, share experiences, and build relationships (Nurmi & Hinds, 2020) to increase their work engagement.

Our results indicate that wearable HRV detectors can help reveal physiological responses that often happen before conscious awareness and may affect performance even though the individual is not aware of them. Therefore, we suggest that wearable HRV detectors could be used to increase awareness of individual's emotional responses and preferences and help employees identify work practices that best support their wellbeing and performance at work. As wearable HRV detectors are becoming more common among employees and health development programs in organizations, we stress the importance of ethical considerations and training in psychophysiology and psychology when applying these technologies. Drawing conclusions about the cardiac data requires triangulation using multiple methods, such as self-reports, field observations, and/or behavioral data because an emotional response consists of three components: physiological arousal, subjective feeling, and motor expression (e.g., facial expression, voice, and gesture). For example, our field observations of the participants' behaviors during different meetings and their self-reports of drowsiness during the observed events enabled us to interpret the temporary decreases in arousal (decreased LF/HF and increased RMSSD) as experienced passive fatigue rather than other possible explanations, such as relaxation, regulation, or recovery (e.g., Aritzeta et al., 2017; Bradley et al., 2010). Therefore, organizational scholars and human resources practitioners using physiological measures in organizational research and development should be trained to use a set of methods to collect and triangulate cardiac, self-report, and behavioral data.

Finally, our study emphasizes ethical concerns in using cardiac measurements in a manner that are helpful rather than harmful for the organizations and their employees. While our data indicate that low-stress arousal creates cognitive flexibility impairment among employees, the use of such sensitive biological information should be carefully considered in organizations. We do not, for example, recommend using these measures for employee selection or screening for ethical and legal reasons. Employees' individual results should be handled confidentially and revealed only to themselves. Employers and managers could then receive aggregate-level results to increase their understanding of how different work contexts, job demands, and resources may influence employee experiences at work.

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Received March 7, 2023
Revision received June 30, 2023
Accepted August 9, 2023 ■