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AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Occupational Health Psychology

ISSN: 1076-8998

2023, Vol. 28, No. 4, 205–223
https://doi.org/10.1037/ocp0000355

Sweet Dreams Are Made of This: A Person-Centered Approach Toward Understanding the Role of Sleep in Chronic Fatigue

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Previous studies show that sleep is essential in preventing symptoms related to chronic levels of fatigue. In the present study, we move beyond the traditional variable-centered approach and adopt a person-centered approach by considering antecedents and outcomes of sleep profiles. Specifically, we consider job characteristics (i.e., workload, job control, and their interaction) as predictors of sleep profiles and indicators of chronic fatigue (i.e., prolonged fatigue and burnout) as outcomes. In establishing sleep profiles, we consider levels as well as the variability of the sleep dimensions across a week. Based on daily diary data from 296 Indonesian employees, the present article uses latent profile analysis to identify sleep profiles based on both weekly averages of several sleep dimensions (i.e., sleep quality, fragmentation, duration, bedtime, and wake-up time) and their intraindividual variability. Moreover, it explores the relationship between the identified profiles to prolonged fatigue and burnout 2 weeks later as outcomes, as well as to baseline workload, job control, and their interaction as predictors. We find four different profiles ("Average Sleepers," "Deep Owls," "Short Sleep Compensators," and "Restless Erratic Sleepers"). While workload, job control, and their interaction could not predict profile membership, these profiles relate differently to prolonged fatigue and burnout. As such, our study shows the importance of understanding the combination of sleep levels and variability across a week through sleep profiles, and how they differentially relate to symptoms of chronic fatigue. Our findings also highlight the need to study indicators of sleep variability alongside sleep levels.

Keywords: sleep, intraindividual variability, burnout, prolonged fatigue, latent profile analysis

Supplemental materials: https://doi.org/10.1037/ocp0000355.supp

After a day of work, employees need to recover to be able to work the next day and to avoid developing chronic levels of fatigue. Sleep is an essential recovery mechanism that helps employees in preventing the consequences of prolonged activation and consequent fatigue (Litwiller et al., 2017; Weigelt et al., 2021). This is important as fatigue can impair employees'—and thus organizations'—optimal functioning through increased psychological distress (Bültmann et al., 2002), performance impairments (Thompson, 2019), accidents (Fang et al., 2015), unethical behavior (Barnes et al., 2011), and sickness absence (Janssen et al., 2003). Insufficient recovery can cause fatigue to build up over time, which can further develop into long-term negative consequences such as burnout (Schaufeli, Desart, & de Witte, 2020), chronic fatigue (Beurskens et al., 2000), and even permanent work disability (van Amelsvoort et al., 2002). To prevent such consequences,

This article was published Online First June 15, 2023.
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The authors thank Michiel Vestjens for programming the Experience Sampling Method software and Rahmadia T. Effendi, Octovi F. Angelia, and Finishia Desela for their help in data collection. They also thank Bona S. H. Hutahaean, Cut N. Kemala, Dewi T. Putri, Fauzia Ramadhaniyanti, Herwansyah, Indira Primasari, Lathifah Hanum, Martina D. Mustika, and Nurul Arbiyah for their help in the translation process. The study was supported by funding from the Beasiswa Pendidikan Pascasarjana Luar Negeri scholarship from the Directorate General of Higher Education, Research, and Technology (T/929/D3.2/KD.02.01/2019; Eka Gatari) of the Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia. The authors have no conflicts of interest to disclose.

An abstract of a prior version of this article was accepted and presented for a symposium in May 2023 at the 23rd European Association of Work and Organizational Psychology Congress in Katowice, Poland.

The extracted data set for the analysis in this article is available upon reasonable request at the DataverseNL and can be accessed at https://doi.org/10.34894/HDH8NS (Gatari et al., 2023). The analysis codes for this study are available through emailing the correspondence author.

Eka Gatari played a lead role in conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, validation, visualization, writing–original draft, and writing–review and editing. Bram P. I. Fleuren played a supporting role in conceptualization, formal analysis, methodology, visualization, writing–original draft, and writing–review and editing and an equal role in supervision. Fred R. H. Zijlstra played a supporting role in conceptualization, methodology, and writing–review and editing and an equal role in supervision. Ute R. Hülsheger played a supporting role in conceptualization, methodology, resources, visualization, and writing–review and editing and an equal role in supervision.

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adequate recovery is indispensable. Sleep plays a core role in enabling adequate recovery (Gatari et al., 2022; Hülsheger, 2016; Litwiller et al., 2017; Rook & Zijlstra, 2006; Weigelt et al., 2021), as the biological processes during sleep allow employees to return to preactivation levels and to "unwind" effectively, so that they can live to perform another day (Litwiller et al., 2017; Mignot, 2008). Therefore, adequate sleep is beneficial for both employees and organizations as it is associated with better self-regulation (Barnes, 2012), fewer work injuries (Barnes & Wagner, 2009), and better performance (Litwiller et al., 2017). However, good sleep can be hard to attain, and the lack thereof results in costs estimated at up to $44.6 billion annually due to sick leave (Casper-Gallup, 2022). Given this difficulty, a better understanding of sleep in relation to symptoms related to chronic fatigue is crucial.

Existing research offers several important insights regarding sleep and fatigue. Sleep is an inherently multidimensional construct with several dimensions that can co-occur at the same time (Buysse, 2014; Matricciani et al., 2018). As an example, sleep duration represents how long people are asleep in one night, sleep quality represents how well they sleep, and sleep timing represents at what time they sleep and wake up (Buysse, 2014; Buysse et al., 1989; Matricciani et al., 2018). Most studies connecting sleep with employees' fatigue have used individual sleep dimensions such as sleep quality and duration (e.g., Hülsheger, 2016; Rook & Zijlstra, 2006). Adopting a variable-centered approach, these studies have looked at how specific sleep dimensions distinctly predict outcomes over other sleep dimensions but do not consider that an employee may experience different combinations of sleep dimensions simultaneously (Matricciani et al., 2018; Shipp et al., 2022). As an example, in 1 week, people may continuously sleep early and have good sleep quality or have erratic bedtime and sleep quality. Other studies consider multiple aspects of sleep (e.g., sleep quality, latency, duration, efficiency, disturbances, medication, and daytime dysfunction) but combine them into one overall index of sleep quality (e.g., Åkerstedt et al., 2014; Loft & Cameron, 2014). By doing so, there is no complete picture of which exact combination of sleep dimensions can explain symptoms of chronic fatigue. For example, will employees with short sleep duration, who sleep at their usual time and have a good sleep quality, have a different chronic level of fatigue than those with longer sleep duration, who sleep outside their usual time and have a poor sleep quality? Consequently, variable-centered approaches do not optimally capture the multidimensional nature of sleep (Matricciani et al., 2018) and thus offer a limited understanding of how sleep relates to fatigue. Sleep researchers outside the organizational sciences have therefore argued that a person-centered approach to studying sleep and its outcomes is urgently needed (Matricciani et al., 2018). Person-centered approaches focus on uncovering distinct subgroups of people who have similar scoring patterns on a set of variables (Bennett et al., 2016; Morin et al., 2020), in this case, aspects of sleep. They enable a better understanding of which exact combination of sleep dimensions can lead to chronic manifestations of fatigue and what role work characteristics play in that.

Another shortcoming of the literature on sleep and fatigue is that it has, to date, focused on levels (trait or state) of sleep and its dimensions, thereby overlooking the variability of sleep and its dimensions over time (e.g., over the course of a workweek). Consequently, the way in which this variability may contribute to chronic manifestations of fatigue beyond sleep levels remains unknown. For instance, over the course of a workweek, Persons A and B may both sleep 7.5 hr per night, on average. Yet, Person A might have had exactly 7.5 hr of sleep every night, whereas Person B might have had 5 days with 5 hr and 2 days with 9 hr. The variability component of sleep dimensions is thus conceptually independent of average sleep levels. Previous studies have highlighted the merits of considering intraindividual variability over time in other areas. For instance, increased intraindividual variability in performance is associated with cognitive decline due to aging and behavioral changes typical to people with Alzheimer's or schizophrenia (MacDonald et al., 2009), intraindividual variability of affect is related to neuroticism (Eid & Diener, 1999), and high intraindividual variability of positive affect can predict poor psychological health above and beyond the average levels of positive affect (Gruber et al., 2013). Therefore, the sleep literature stands to benefit from considering variability in sleep dimensions in addition to their levels when adopting person-centered approaches. Considering the variability of sleep and its dimensions is all the more important as social and work demands have been shown to contribute to the variability of sleep patterns (Bei et al., 2016; Rook & Zijlstra, 2006).

Therefore, the goal of the present study is to adopt a person-centric perspective in studying the role of sleep for chronic fatigue. In doing so, we consider sleep as a multidimensional construct and consider levels of five sleep dimensions (i.e., sleep duration, quality, bedtime, wake-up time, and fragmentation) and their intraindividual variability over 1 week using latent profile analysis (LPA). Building on the effort–recovery model (Meijman & Mulder, 1998), we relate these profiles to indicators of chronic fatigue assessed 2 weeks later (i.e., prolonged fatigue and burnout). Additionally, in an effort to shed light on the role of work in sleep profiles, we build on the job demand–control (JDC) model (Karasek, 1979) and study workload and job control at baseline as predictors of profile membership.

With the aforementioned approach, this article contributes to the literature on sleep and fatigue among workers in three important ways. First, this study contributes to theory development on the relationship between sleep and fatigue by moving away from a variable-centered approach and introducing a person-centered approach. This contribution is important, as sleep dimensions do not exist in isolation but coexist in patterns that can be beneficial or harmful for employees' fatigue. Second, the study draws attention to the role of dynamic characteristics of sleep by incorporating intraindividual variability of sleep dimensions and incorporating these in the person-centered approach. Recognizing the dynamic nature of sleep is important, because compensation effects may occur over time and not recognizing this possibility limits our understanding of sleep and fatigue. Third, this study contributes to the wider occupational literature that has witnessed a surge of interest in adopting person-centric approaches when studying phenomena such as recovery from work (e.g., Bennett et al., 2016; Chawla et al., 2020), temporal focus (Shipp et al., 2022), or emotional labor (Gabriel et al., 2015). Our study adds to this and highlights the possibilities and merits of a person-centered approach in studying sleep specifically. Furthermore, we showcase that considering combinations of average levels and variability of variables of interest enriches such person-centered approaches.

Fatigue and Its Chronic Manifestations

Fatigue has been a focus in studies on employee health as it is related to both employee and organizational outcomes (Bültmann et al., 2002; Fang et al., 2015; Janssen et al., 2003; Thompson, 2019). In general, fatigue in the work context can be described as "tiredness and reduced functional capacity that is experienced during and at the end of the workday" (Frone & Tidwell, 2015, p. 274). Fatigue usually comes after someone exerts themselves to do something, and longer exertion means further fatigue (Meijman & Mulder, 1998). Fatigue varies in severity—it can be mild and easy to reverse by resting or switching tasks or severe and hard to reverse even after resting or switching to other tasks (Beurskens et al., 2000). This severe form of fatigue is often referred to as prolonged fatigue, and it can impair employee functioning because it lasts for 14 days or more (Beurskens et al., 2000). Usually, an individual associates the cause of prolonged fatigue with health symptoms (Huibers et al., 2003; Leone et al., 2007). Aside from feeling fatigued longer, employees with prolonged fatigue may feel severe exhaustion and find it difficult to do physical activities (Beurskens et al., 2000; Huibers et al., 2003).

Another type of severe fatigue that is more related to work is burnout (Leone et al., 2007). Burnout is characterized by four core symptoms such as exhaustion, difficulty in regulating emotional and cognitive processes, and mental distance due to work aversion (Schaufeli, de Witte, & Desart, 2020). Burnout is further explained as a syndrome with four dimensions as the core symptoms (Schaufeli, Desart, & de Witte, 2020; Schaufeli, de Witte, & Desart, 2020). The first dimension is exhaustion, that is, extreme tiredness physically and mentally (Schaufeli, de Witte, & Desart, 2020. The second dimension is cognitive impairment, which is indicated by problems related to memory, attention, concentration, and poor overall cognitive performance. The third dimension is emotional impairment, that is, showing intense emotional reactions and feeling emotionally overwhelmed. The last dimension is mental distance, that is, distancing oneself from work psychologically, such as avoiding working on tasks and feeling reluctant to work (Schaufeli, de Witte, & Desart, 2020). Exhaustion, cognitive impairment, and emotional impairment represent the inability to invest energy in different areas, whereas mental distance represents an aversion to invest energy (Schaufeli, Desart, & de Witte, 2020). The core symptoms may also be accompanied by secondary symptoms such as depressed mood, psychological distress (i.e., nonphysical symptoms caused by psychological problems), and psychosomatic complaints (i.e., physical complaints caused by or exacerbated by psychological problems; Schaufeli, de Witte, & Desart, 2020). Understanding burnout is crucial as burnout can impair employees' abilities to cope with work stressors adequately (Bakker et al., 2023; Fleuren et al., 2023).

Burnout and fatigue can co-occur, leading to worse negative symptoms (Leone et al., 2007). Unlike prolonged fatigue, an individual usually associates the cause of burnout with psychological rather than physical health issues (Huibers et al., 2003). Both burnout and prolonged fatigue are important to consider as both represent a condition caused by prolonged stressors (Beurskens et al., 2000; Schaufeli, Desart, & de Witte, 2020) but are distinct enough from each other as they are connected to two different sources (general health for prolonged fatigue and workplace for burnout; Leone et al., 2007).

The effort–recovery model by Meijman and Mulder (1998) gives insights into how the two severe forms of fatigue can result from working. In general, employees feel fatigued after exerting effort in handling daily job demands and stressors at work (Meijman & Mulder, 1998). Employees need to spend time off work to recover and return to prework activation states, so they can maintain a sustainable work life in the long term (Fleuren et al., 2020). When employees have enough time to recover from their work-induced fatigue, fatigue does not become problematic. However, fatigue can accumulate when insufficient recovery takes place, resulting in a lasting undesirable effect on effort expenditure (Meijman & Mulder, 1998). Therefore, proper recovery through sleep is essential to prevent burnout and prolonged fatigue.

Sleep

Sleep is perhaps the most crucial mechanism in recovering from work-induced fatigue (de Lange et al., 2009; Weigelt et al., 2021). Sleep can be described as an immobile state and significantly reduced responsiveness to stimuli that can relatively be quickly reversed (Siegel, 2005). Through this reduced activity and responsiveness, organisms can return to a state of homeostasis (Mignot, 2008), such that at a later moment, they can resume activity without incurring damage. During a good night's sleep, the biological processes in the body can help recovery, such as restoring cellular components needed for bodily functions and lower energy expenditure for recovery (Mignot, 2008). By recovering through sleep, employees will feel less fatigued (Litwiller et al., 2017), find it easier to regulate and control themselves (Barnes, 2012; Barnes et al., 2011), and function better in various domains of work (Barnes & Wagner, 2009; Barnes et al., 2011, 2013).

How someone sleeps is explained by the two-process model of sleep regulation, that distinguishes between Process S and Process C (Borbély, 1982). Process S, or the homeostatic process, explains that sleep pressure is heightened the longer someone is awake and lessened following an adequate, deep sleep. Inadequate sleep will incur sleep debt that needs to be compensated. Process C, or the circadian process, refers to the sleep process governed by circadian rhythm. Process C is helped by external cues (e.g., the light–dark cycle and social constraints) and internal cues from the individual's biological clock. An individual usually feels sleepier in the evening and more awake in the morning, and it is harder to sleep well outside the optimal time (Åkerstedt et al., 2005). Each individual may have a different homeostatic sleep pressure dissipation rate and circadian rhythm, thus creating interindividual differences in sleep rhythm (Waterhouse et al., 2012).

As sleep constitutes a process, researchers have attempted to describe it using multiple distinct dimensions. Dimensions refer to co-occurring aspects of sleep that provide conceptually distinct pieces needed to comprehensively capture sleep (e.g., quality, duration, timing). This study focuses on sleep duration, quality, timing, fragmentation, and intraindividual variability among the aforementioned sleep dimensions. These dimensions are chosen as they represent key mechanisms of sleep related to the sleep regulatory process that may help employees in fatigue recovery across the week. The next subsection describes the importance of each dimension.

From Sleep to Sleep Dimensions

How much a person sleeps, or sleep duration, is important so that an individual can get through the necessary sleep stages (Buysse, 2014) and proper sleep pressure dissipation in Process S. Studies found that sleep duration outside 7–8 hr is usually related to unfavorable outcomes. Long sleep duration (≥9 hr of sleep) and disturbed sleep are found to be related to higher allostatic load (Clark et al., 2014) and poor health outcomes (e.g., higher mortality, cardiovascular diseases, and stroke; Jike et al., 2018). Conversely, a chronic restriction of sleep (≤6 hr per night) is associated with declining cognitive performance (van Dongen, Maislin et al., 2003) and a higher risk of having cardiovascular disease (Williams et al., 2021). Researchers typically operationalize sleep duration in two different ways: how long individuals are on their bed, trying to sleep, and wake up (time in bed) or how long the individuals actually sleep (total sleep time; e.g., Rook & Zijlstra, 2006). This study focuses on the actual sleep time as it captures how long individuals really sleep.

Sleep timing is another important dimension in describing sleep comprehensively that refers to when people sleep, which also relates to Process C. Specifically, sleep timing consists of the time when people go to sleep and the time when they wake up. While the body regulates the optimal time to sleep through circadian rhythm, individuals can sleep not at the ideal time due to external pressure such as work or social schedule (Bei et al., 2016). In general, later bedtime is associated with poor physical and mental health outcomes, though the results are mixed (Chaput et al., 2020). Earlier wake-up time is associated with more positive affect and health, possibly because it adheres better with an early start in most work schedules and allows more morning sunlight exposure (Biss & Hasher, 2012). The effect of sleep timing is more pronounced in night shift workers as they sleep when the circadian system of their body promotes wakefulness, which is also related to less optimal cognitive functioning (Åkerstedt & Wright, 2009). Both bedtime and wake-up time are included as dimensions in the profiles, as both dimensions are important to describe sleep timing and have been associated with physical and mental health outcomes.

While the body can promote sleep through Process S and C, external and internal factors can disturb this process to run optimally. These disturbances make individuals still feel sleepy and unrestored upon wakening, which signifies a poor sleep quality (Harvey et al., 2008). Poor sleep quality can happen due to hyperarousal that overrides sleep pressure from Process S and C, signified by a person still feeling alert and active nearing bedtime (Benoit & Aguirre, 1996). Hyperarousal happens due to external factors (e.g., other things more interesting or important than sleep) or internal factors (e.g., anxiety, neuroticism, or heightened emotional reactivity; Benoit & Aguirre, 1996). In general, sleep quality is one of the most important sleep dimensions, as it explains some sleep correlates better than sleep duration (e.g., depression, fatigue, general strain, and work–family conflict; Litwiller et al., 2017). Sleep quality can be defined as the individual's assessment of whether their sleep is poor or good (Buysse, 2014).

Sleep fragmentation represents an important final dimension in describing sleep. Sleep fragmentation refers to the interruption of sleep, characterized by brief episodes of wakefulness (National Institutes of Health, 2011). In that sense, sleep fragmentation connects closely to the experienced quality of sleep, but it uniquely describes the extent of (un)interruptedness of sleep. Interruptions of sleep (as reflected in sleep fragmentation) can disturb essential sleep phases such as slow-wave sleep and rapid eye movement sleep and thereby heighten exhaustion (Hursel et al., 2011). As it disturbs sleep phases, it also disturbs Process S, as the homeostatic sleep pressure dissipates during slow-wave sleep (Mongrain & Dumont, 2007). Sleep fragmentation can be captured by how often an individual wakes up at night (Buysse et al., 1989).

In summary, the five dimensions of sleep duration, sleep onset time, waking time, sleep quality, and sleep fragmentation seem to paint a complete picture of sleep characteristics to build profiles. They cover distinct and relevant aspects of sleep that do not represent extremities (e.g., such as clinical insomnia) and thus can be expected to show considerable within- and between-person variation in general working populations.

Beyond Levels: Intraindividual Variability of Sleep Dimensions

Even when sleep rhythm is regulated through Process S and C, sleep fluctuates considerably within persons between days (Rook & Zijlstra, 2006; Waterhouse et al., 2012). Sleep researchers outside the organization sciences have therefore highlighted the importance of considering intraindividual variability of sleep (Bei et al., 2016; Chaput et al., 2020; Matricciani et al., 2018). Yet, surprisingly, variability in sleep dimensions has been largely overlooked in the organizational sleep literature. Intraindividual variability is how different an individual's level is from one time to another (Bei et al., 2016). Sleep can fluctuate naturally due to the different light–dark exposure between days and slight variations in the body clock (Waterhouse et al., 2012). Furthermore, other factors such as different social and work schedules, especially between weekends and weekdays, can affect sleep duration and timing (Wittmann et al., 2006). Sleep quality and fragmentation can also fluctuate depending on the day of the week, the anticipation of the work demands, and the opportunities to rest (Hülsheger et al., 2014; Rook & Zijlstra, 2006; Weigelt et al., 2021).

There is incipient evidence from non-work-related research on the importance of intraindividual variability in sleep dimensions. For instance, indicators of poor mental and physical health were associated with intraindividual variability of total sleep time and sleep timing (Bei et al., 2017), time in bed (Geoffroy et al., 2014), and fragmentation (Dzierzewski et al., 2020). A previous study shows that intraindividual variability of sleep can contribute to outcomes beyond the average scores of sleep by demonstrating that sleep duration variability predicts obesity in older people while controlling for the level of sleep duration (Patel et al., 2014). However, studies on intraindividual variability of sleep remain restricted to a limited set of sleep dimensions and typically do not include the level of sleep variables as a confounder (for an in-depth review, see Bei et al., 2016). Importantly, these studies have taken a variable-centered rather than a person-centered approach (Bei et al., 2016), and the variability of sleep dimensions has, to our knowledge, been widely overlooked in the occupational health literature.

Given the benefits of including intraindividual variability of sleep, this study includes the intraindividual variability of all the sleep dimensions measured when estimating sleep profiles. That is, day-to-day variation in the duration, quality, bedtime, wake-up time, and fragmentation across 1 week are incorporated as variables. One week is an appropriate time frame for sleep profiles that incorporate day-to-day variation, as it represents the typical work cycle of working during weekdays and being off during weekends (Hülsheger et al., 2022; Rook & Zijlstra, 2006). As such, incorporating variability for the sleep dimensions as variables in estimating the sleep profiles make for a theoretically sound way of handing within-person variation over the meaningful time period of 1 week.

From Sleep Levels and Variability to Sleep Profiles

The present study adopts a person-centered approach and aims to add to the sleep literature by studying sleep profiles, that is, the unique combination of sleep duration, quality, bedtime, wake-up time, and fragmentation with each of their intraindividual variability across a week, and their relation to the chronic manifestation of fatigue (prolonged fatigue and burnout) and also work-related predictors (workload and job control) using LPA. The person-centered approach has the advantage of finding natural subgroups with similar variable combinations patterns (Morin et al., 2018). The subgroups can show quantitatively distinct profiles (different indicator levels), which means that all indicators are high or low (Gabriel et al., 2015; Marsh et al., 2009; Shipp et al., 2022). For example, the employees within a profile have a long sleep duration, better sleep quality, frequent sleep fragmentation, late sleep time, and late wake-up time with high variation within a week. It can also show qualitatively distinct profiles (different shapes), which means that the indicators have varying levels within a person (Gabriel et al., 2015; Marsh et al., 2009; Shipp et al., 2022). For example, short sleep duration, poor sleep quality, frequent sleep fragmentation, late sleep time, and early wake-up time with low variation within a week. In contrast, the variable-centered approach could not identify these quantitative and qualitative differences, which means that some meaningful combination of variables may be overlooked (Gabriel et al., 2015). Therefore, the person-centered approach has the advantage of illustrating various subgroups that show how sleep levels and their variability can naturally combine.

By using these subgroups, the person-centered approach provides the possibility of understanding how the combinations of these variables can explain outcomes. As an example, initial studies outside the organization sciences adopting a person-centered approach revealed that certain sleep profiles can predict important outcomes, such as cognitive functioning (Ownby et al., 2014), life satisfaction, and chronic illness (Smith & Lee, 2022). While the studies have shown the benefits of using a person-centered approach, these studies do not sufficiently explore how sleep profiles can then explain the manifestation of the chronic level of fatigue and the effects of work on sleep profiles.

Person-centered approaches follow an inductive approach without formal predictions on what kind of profiles will emerge (Morin et al., 2018). We therefore do not formulate specific hypotheses. However, some broad expectations can be made. Accordingly, we expect to find subgroups with consistently healthy sleep patterns across the week (i.e., low intraindividual variability of sleep with good sleep value on average), varying sleep patterns across the week, and, last, consistently unhealthy sleep patterns (i.e., low intraindividual variability of sleep with poor sleep value on average) across the week.

As the main purpose of looking at sleep in the context of employees is to prevent fatigue accumulation and burnout, we connect these profiles that emerge to prolonged fatigue and burnout. Aligned with the effort–recovery model, fatigue may accumulate over time if employees continuously cannot recover well (Meijman & Mulder, 1998). Sleep is closely related to well-being (Meijman & Mulder, 1998) because of the biological processes during sleep that enable employees to recover better (Mignot, 2008; Poe, 2017). If employees continue to have sleep difficulties over time, they will have fewer opportunities to recover, which may predict a more severe form of fatigue (Ekstedt et al., 2006). Therefore, we expect that employees with stable, healthy sleep profiles across the week have a significantly lower score of prolonged fatigue and burnout than other sleep profiles.

The study also explores whether there are differences in each burnout core symptom dimensions and also burnout secondary symptoms aside from the overall burnout core symptoms and prolonged fatigue. Each burnout core symptom dimensions reflects either inability to work in different kinds of areas or reluctance to work. Burnout secondary symptoms reflect more severe symptoms of burnout (psychosomatic complaints and psychological problems), which also show how much help employees need (Schaufeli, Desart, & de Witte, 2020). Each of these dimensions reflects distinct symptoms in different areas and can occur at different levels within people (Schaufeli, Desart, & de Witte, 2020). For example, an employee can have high exhaustion and mental distance levels but only medium emotional and cognitive impairment. By separating the analysis of each of the core symptoms and secondary symptoms, the study provides a comprehensive picture whether the sleep combinations can explain problems due to general health issues (through prolonged fatigue) and work-related issues (through burnout core and secondary symptoms). We then specify whether sleep can only explain certain burnout symptoms using burnout core symptoms dimensions, which show either inability to work properly in specific areas or an aversion to work.

> *Research Question 1:* Which different weekly sleep profiles exist?

> *Research Question 2:* How do the weekly sleep profiles predict overall burnout core symptoms, burnout core symptoms dimensions, burnout secondary symptoms, and prolonged fatigue?

Work-Related Antecedents of Sleep Profiles

After identifying sleep profiles and connecting them to indicators of chronic fatigue, this study further tests antecedents of the sleep profiles to give further insight into the role of work in sleep profile membership. Drawing on the effort–recovery model (Meijman & Mulder, 1998), effort exerted from facing job demands can cause stress reactions. This reaction might trigger hyperarousal (Benoit & Aguirre, 1996), which then disturbs employees' sleep. Relevant work predictors that may cause such reactions can best be drawn from established work characteristics that are known to create job strain.

As such, drawing on the JDC model (Karasek, 1979), we consider the demandingness of the job as well as the control that employees have in it as relevant load-inducing factors (de Lange et al., 2009; Litwiller et al., 2017). Specifically, job demands are sources of stress from work, whereas job control reflects how much control employees have over their tasks and conduct at work (Karasek, 1979). Workload can be defined as employees' perception of their amount of work, either in pace or volume (Spector & Jex, 1998). Employees with a high workload may have less time to sleep and sleep unwell because they think about their work during bedtime hours (de Lange et al., 2009). In the meta-analysis by Litwiller et al. (2017), workload is the only variable that predicts sleep quality and duration. For job control, the study used the definition by Morgeson and Humphrey (2006), that is, "the extent to which a job allows freedom, independence, and discretion to schedule work, make decisions and choose the methods used to perform tasks" (p. 1323). There are three dimensions of control: work scheduling, decision-making, and work methods (Morgeson & Humphrey, 2006). Employees with more control over their job can better strategize how to recover better from fatigue (Kubo et al., 2016), such as opting for more sleep.

The JDC model also explains that strain does not result only from either only job demands or control but the combination of the two aspects (Karasek, 1979). That is, when job demands are high and job control is low, then employees will feel high job strain. If employees have low job demands and high job control, they will feel low job strain (Karasek, 1979). Thus, looking at job demands or control when predicting profile membership will not suffice. Aligned with the JDC model, employees with low job strain (i.e., low job demands and high job control) have better sleep quality (de Lange et al., 2009). This may also reflect in the overall sleep combination, in which employees with low job strain will be in a profile that reflects better sleep, whereas employees with high job strain will be in a profile that reflects poor sleep.

> *Research Question 3:* How do workload, job control, and the interaction between workload and job control predict weekly profile membership?

Method

Study Design

The present study was a part of a larger data collection effort consisting of a 3-week shortitudinal daily diary study, which was approved by a local ethics review committee (No. ERCPN-233_10_02_2021). Due to high levels of missing data in the second and third week, the present study used data from week one only. The baseline questionnaire included demographics (e.g., age and gender) and job characteristics (e.g., job demands and control); the 3-week daily diary study included daily measures for the sleep dimensions; and the final questionnaire covered distal outcomes (e.g., fatigue and burnout), which was measured the day after the 3-week daily questionnaire ended (i.e., 2 weeks after Week 1).

Sample

Two hundred ninety-six Indonesian full-time employees working regular daytime jobs formed the final sample of the study. These participants were recruited mainly through snowball sampling. That is, the invitation for the study was shared with the network of the researchers and asked to be reshared by participants, nonparticipating individuals, and Human Resources managers who were part of the network. For Human Resources managers effectively spreading the survey among colleagues, there was a possibility of receiving a customized organizational report if a sufficient number of participants in that organization was reached to guarantee anonymous reporting. The only potential gain for individuals participating in the study was winning a monetary voucher or an ebooklet regarding employees' well-being (see Procedure section). Following recommendations for handling missing data, all participants who had at least completed the daily survey once were retained (Newman, 2014; Peugh & Enders, 2004; van Buuren, 2018; Wang et al., 2017).[1] The final sample of 296 employees was achieved by excluding one double entry and 70 entries for which no complete daily morning responses were recorded from the initial 367 qualified respondents. In total, we received 1,559 daily survey responses nested across 7 days, nested in 296 participants, with an average amount of 5.27 daily surveys per person. Consequently, the response rate for the daily surveys in the final sample was 75.24% out of 2,072 possible daily surveys. The supplemental material contains a more detailed description of the response rate of the participants. Most of the participants were either in their 20s (44%) or 30s (41%), female (64%), lived without their partners (58%), and had no child at home (64%). The participants came from a variety of industries, predominantly from education and higher education (30%), finance and insurance (12%), and the government (11%). The sample also consisted of participants from various occupation types, with the top three working as human resources (22%), lecturers and teachers (14%), and IT (13%).

Procedure

Individuals interested in the study first received an information letter describing the nature of the study, participants' rights, data security measures, and guarantee of anonymity. Subsequently, individuals willing to participate signed the informed consent and started participating in the study with the baseline questionnaire. After the baseline questionnaire, they received invitations by email for the bidaily (i.e., morning and evening) questionnaires during the next 21 days and the final questionnaire the day after the last daily questionnaire. There was no time restriction to complete the baseline questionnaire, but to keep the timing of the daily questionnaires comparable, participants would always start the first daily questionnaire the first Monday after finishing the baseline. For the daily morning and before-bed questionnaires, response time windows ranged from 05:00 a.m. to 13:00 p.m. and 19:00 p.m. to 03:00 a.m., respectively. Participants were required to complete the final questionnaire within 7 days of their final daily measurement, regardless of their level of participation in the preceding daily questionnaires. At the end of the study, participants were offered an ebooklet about employee well-being and the possibility to enter a raffle with 31 prizes. An exception was made for 25 employees participating from an organization with no monetary reward policy, which only received the ebooklet. Participants would be eligible to win better valued rewards based on the number of questionnaires they completed. The lowest tier reward was Rp. 100,000 (approximately $7), and the highest tier reward was Rp. 1,000,000 (approximately $70).

Measurement

All questionnaires in the study were presented to participants in Indonesian. As most of the measures did not have a validated Indonesian version, English-validated versions were translated using the back-translation procedure (for descriptives and Cronbach's αs of scales, see Table 1).

[1] Missing data can rarely be assumed to be missing at random. Statisticians strongly advise against traditional practices of using listwise deletion because this produces biases and yields inaccurate standard errors (Newman, 2014; Peugh & Enders, 2004; Wang et al., 2017). In line with more recent research (Hülsheger et al., 2021; Wehrt et al., 2022), we therefore followed their advice and retained all participants with missing data and used multiple imputation as a modern missing data technique instead (Newman, 2014; Peugh & Enders, 2004; Wang et al., 2017).

Table 1

Means, Standard Deviations, and Intercorrelations Between Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1. Age	32.26	8.14	—																							
2. Gender	—	—	−.10	—																						
3. Workload	3.49	.80	−.04	.06	(.86)																					
4. Work scheduling control	3.86	.72	.17**	.06	−.09	(.82)																				
5. Decision-making control	3.47	.81	.20**	−.01	.09	.56**	(.82)																			
6. Work method control	3.69	.71	.17**	−.01	−.06	.60**	.69**	(.80)																		
7. Job control	3.67	.64	.21**	.02	−.02	.83**	.88**	.88**	(.89)																	
8. *M* sleep quality	2.90	.32	.17**	−.05	−.10	.17**	.11	.15*	.17*	—	−.27**	.19**	−.09**	.02												
9. *M* sleep fragmentation	1.03	.80	.02	.14*	.14*	.01	.08	.06	.06	−.37**	—	−.01	−.12**	.04												
10. *M* sleep duration	6.24	1.07	−.18**	.21**	−.07	.10	.00	.08	.07	.17*	.00	—	−.46**	.68**												
11. *M* bedtime	23.02	1.20	−.30**	.05	.07	.04	.05	.04	.05	−.15*	−.14*	−.13*	—	.22**												
12. *M* wake time	5.94	1.44	−.38**	.20**	.04	.12*	.07	.08	.10	−.16*	.03	.53**	.69**	—												
13. *SD* sleep quality	.39	.26	.04	−.02	.12	.04	.17*	.12	.13	−.33**	.25**	−.11	.00	.03	—											
14. *SD* sleep fragmentation	.83	.44	−.07	.14*	.05	.04	.06	.07	.07	−.30**	.65**	−.05	−.002	.06	.28**	—										
15. *SD* sleep duration	1.41	.67	−.02	−.01	−.01	−.002	.08	.01	.03	−.13	.15*	−.23**	.03	−.07	.18**	.24**	—									
16. *SD* bedtime	.97	.46	−.10	.01	.02	.09	.10	.08	.11	−.07	.03	−.06	.27**	.19**	.11	.15*	.39**	—								
17. *SD* wake time	1.14	.66	−.04	−.11	−.02	−.09	−.03	−.05	−.06	−.06	.02	−.27**	.08	−.09	.13	.14*	.69**	.18**	—							
18. Prolonged fatigue[a]	2.74	.70	−.20**	.10	.25**	−.06	−.03	−.06	−.06	−.32**	.22**	−.06	.22**	.18**	.23**	.24**	.06	.19**	.15*	(.90)						
19. Exhaustion[b]	2.71	.72	−.21**	.10	.28**	−.04	−.10	−.07	−.08	−.23**	.16*	−.04	.18**	.15*	.19*	.23**	.07	.19**	.11	.64**	(.76)					
20. Mental distance[b]	2.35	.87	−.25**	.05	.11	−.18**	−.19**	−.15*	−.20**	−.22**	.13	.02	.20**	.23**	.07	.16*	.06	.11	.11	.39**	.51**	(.81)				
21. Cognitive impairment[b]	2.42	.75	−.28**	.13	.09	−.04	−.01	−.01	−.02	−.17*	.11	−.04	.27**	.22**	.12	.19*	.04	.12	.13	.49**	.49**	.61**	(.85)			
22. Emotional impairment[b]	1.88	.70	−.16*	−.14*	.02	−.18**	−.13*	−.08	−.15*	−.16*	.08	−.02	.09	.07	.17*	.10	.01	.10	.13	.40**	.40**	.40**	.39**	(.80)		
23. Burnout core symptoms[b]	2.34	.59	−.29**	.05	.16*	−.14*	−.14*	−.10	−.15*	−.25**	.16*	−.02	.24**	.22**	.17*	.22**	.06	.17*	.15*	.61**	.77**	.84**	.81**	.69**	(.88)	
24. Burnout secondary symptoms[b]	2.40	.61	−.23**	.15*	.20**	−.03	.00	−.04	−.02	−.22**	.20**	−.08	.30**	.25**	.15	.23**	.07	.10	.11	.60**	.64**	.47**	.54**	.47**	.68**	(.85)

Note. $N = 296$. Cronbach's α is displayed in parentheses on the diagonal. Correlation of the variables from age until *SD* wake time used multiple imputation data sets, whereas correlation with the outcomes used listwise deletion. Correlations below diagonal were between-level correlations ($n = 225$–296), whereas correlations above diagonal were within-level correlations ($n = 2{,}072$). Gender was dummy-coded 0 = male and 1 = female.

[a] $N = 227$. [b] $N = 225$.

* $p < .05$. ** $p < .01$.

Sleep Dimensions

All sleep dimensions (i.e., sleep quality, bedtime, wake-up time, fragmentation, and duration) were captured with the daily morning questionnaire. Sleep quality was assessed using a single item, "How do you evaluate this night's sleep?" (Buysse et al., 1989), which had previously been used in daily diary studies (e.g., Hülsheger, 2016; Sonnentag et al., 2008). Participants responded to this question using a 4-point Likert scale, that is, *very bad*, *bad*, *good*, and *very good*. The items for bedtime, wake-up time, and fragmentation were adapted from the Pittsburgh Sleep Quality Index (Buysse et al., 1989) to make the items fit a daily diary format and be understandable for Indonesian participants (bedtime: "At what time did you try to sleep yesterday?"; wake-up time: "At what time did you wake up today?"; and fragmentation item: "How many times was your sleep interrupted because you woke up?"). Sleep duration was calculated by subtracting wake-up time and two items measuring sleep latencies (sleep onset latency: "From the moment you tried to sleep, how long did it take for you to fall asleep?" and duration of wake after sleep: "How long was your sleep interrupted?") from bedtime, to arrive at the actual time respondents slept while being in bed.

Prolonged Fatigue

Prolonged fatigue was measured in the final questionnaire using eight items from Checklist Individual Strength, specifically the subjective fatigue subscale (e.g., "I get tired very quickly" and "I feel weak"; Beurskens et al., 2000; Vercoulen et al., 1994). The participants reflected on what they felt during the past 2 weeks and responded using a 5-point Likert scale, with anchors ranging from 1 = *strongly disagree* to 5 = *disagree*.

Burnout

Burnout was measured in the final questionnaire using the 12–item short version of the Burnout Assessment Tool–12 (BAT-12) by Schaufeli, Desart, and de Witte (2020). The BAT has demonstrated reliability in seven national samples (de Beer et al., 2020). The BAT-12 consisted of four dimensions for the core symptoms, that is, exhaustion (e.g., "At work, I feel mentally exhausted"), mental distance (e.g., "I feel a strong aversion towards my job"), emotional impairment (e.g., "At work, I feel unable to control my emotions"), and cognitive impairment (e.g., "I make mistakes in my work because I have my mind on other things"), with three items for each dimension. The measurement consisted of five items for each of the secondary symptoms, that is, psychosomatic (e.g., "I suffer from headaches") and psychological complaints (e.g., "I feel tense and stressed"). The participants could respond using a 5-point Likert scale, with anchors ranging from 1 = *never* to 5 = *always*.

Workload

Workload was measured at baseline using four items from the workload scale of the Job Stress Questionnaire (Caplan et al., 1975; e.g., "How often does your job require you to work very hard?"). Anchors ranged from 1 = *strongly disagree* to 5 = *strongly agree*.

Job Control

Job control was measured at baseline using the job autonomy dimensions of the Work Design Questionnaire (Morgeson & Humphrey, 2006). There were three items for each dimensions, that is, work scheduling autonomy (e.g., "The job allows me to make my own decisions about how to schedule my work"), decision-making autonomy (e.g., "The job gives me a chance to use my personal initiative or judgment in carrying out the work"), and work methods autonomy (e.g., "The job allows me to make decisions about what methods I use to complete my work"). The participants responded to the statements with 5-point Likert options, with anchors ranging from 1 = *strongly disagree* to 5 = *strongly agree.*

Analyses Strategy and Procedure

Before the LPA, we applied state-of-the-art techniques to handle missing data for the day-level sleep dimensions. Specifically, we used the multiple imputation by chained equations approach with the multiple imputation by chained equation package 3.14 in R (van Buuren & Groothuis-Oudshoorn, 2011). This approach has been recognized as one of the optimal ways for handling missing data (Newman, 2014; Tan et al., 2018; van Buuren, 2018). We used this multiple imputation approach specifically, as it was necessary to calculate the averages and standard deviations from the imputed data before profiles could be estimated. Consequently, we did not have the possibility of using alternative approaches, such as full information maximum likelihood, as this approach is only possible when the model of interest is directly estimated (Newman, 2014). As the missing data for the day-level sleep indicators followed a multilevel structure, the imputation model was constructed following recommendations by Tan et al. (2018). As the set included 27% missing data, we generated 27 different data sets for the LPA through 20 iterations (van Buuren, 2018). For linking the profiles from our LPA to our target outcomes (i.e., prolonged fatigue and burnout), we could not use the same missing data handling technique as this would likely bias our associations between profiles and outcomes (Asparouhov & Muthén, 2021). For this part of our analyses, we therefore applied listwise deletion for missing data handling instead.

The first part of our analysis involved identifying sleep profiles based on diary data with LPA in Mplus 8 (Muthén & Muthén, 1998/2017), following steps described by Morin et al. (2020). The first step is determining how many profiles fit the data (i.e., profile enumeration), starting from a one-profile solution. The number of profiles was increased until there was little improvement in the model fit. Three information criterions (ICs) were used to see which profiles fit the best: Akaike IC (AIC), Bayesian IC (BIC), and sample size–adjusted BIC (SABIC). The best profile solution had smaller AIC, BIC, and SABIC than other profile solutions (Morin et al., 2020). The elbow plots of these information criteria were also used to see which profile the improvement stops decreasing the most (Nylund-Gibson & Choi, 2018). Aside from the ICs, each profile should have a decent number of individuals (more than 5%–8% of the sample). The profiles should also be theoretically meaningful (Nylund-Gibson & Choi, 2018). As the sample size was relatively small, BIC was one of the main considerations for the profile enumeration (Tein et al., 2013). Then, for the first step of the LPA, profile enumeration, the model was first run with the means and variances freely estimated. If the model would not converge, the variances were constricted to be equal across the profiles while allowing the means to be freely estimated (Morin et al., 2020). The second step of the analysis consisted of a direct inclusion approach to analyze whether participants in different sleep profiles had different burnout and prolonged fatigue scores. In direct inclusion, the outcome variable was directly included in the model-building process, and as it only needed one step, it was an effective option for analyzing the model (McLarnon & O'Neill, 2018). When the missing data were in the profile indicators, other options such as Bolck-Croon-Hagenaars analysis needed an information (e.g., weights) to be analyzed for each imputed data set manually before running the outcome analysis, which was not as effective as direct inclusion (Asparouhov & Muthén, 2021). The third and final step of our analyses was a multinominal regression to predict profile membership with the two work characteristics. This analysis was performed using a three-step approach, that is, R3STEP (i.e., multinomial regression) in Mplus 8.4 (Muthén & Muthén, 1998/2017) to analyze whether workload and job control predicted the probability of certain sleep profile membership. Aside from the estimates, the study also reported odd ratios of the R3STEP results (Bennett et al., 2016). Unlike the outcome analysis, the three-step approach could run the predictor analysis automatically when the missing data were in the sleep indicator. To avoid the profiles shifting during the second and the third steps, user-defined starting values were set for each profile before running the analysis (McLarnon & O'Neill, 2018; Morin et al., 2020). Starting values were the values used to start building the model, which the software provided automatically through random starting values (Muthén & Muthén, 1998/2017). Among the random starting values sets, the optimal starting values could be obtained after finding the final optimal unconditional model, which can then be used as the user-defined starting values (McLarnon & O'Neill, 2018).

Results

We first considered several descriptives for our main variables to describe our sample scoring patterns, correlations, and quality of our measurement instruments. Table 1 shows the correlation between the study variables, descriptives, and Cronbach's α. The Cronbach's αs indicated that the adapted multi-item measures in our study had good reliabilities, both for the dimensions and the higher order constructs where applicable (Table 1). Besides estimating internal consistencies for our measures, we ran confirmatory factor analyses using Mplus 8.4 (Muthén & Muthén, 1998/2017) to assess the dimensionality and measurement quality of our different multi-item instruments. As reported elaborately in the supplemental materials, the best-fitting model included 11 first-order factors underlying the items for each of the scales (i.e., workload, work scheduling control, decision-making control, work method control, prolonged fatigue, exhaustion, mental distance, cognitive impairment, emotional impairment, psychological complaints, and psychosomatic complaints) with correlations between the factors (χ^2 = 1138.70, comparative fit index [CFI] = .94, Tucker–Lewis index [TLI] = .93, root-mean-square error of approximation [RMSEA] = .04, standardized root-mean-square residual [SRMR] = .06). An alternative model that included second-order factors (i.e., job control, burnout core symptoms, and burnout secondary symptoms) underlying their dimensions as first-order factors (i.e., work scheduling control, decision-making control, and work method control for job control; exhaustion, mental distance, cognitive impairment, and emotional impairment for burnout core symptoms; and also psychosomatic and psychological complaints for burnout secondary symptoms) also showed a good fit (χ^2 = 1264.80, CFI = .92, TLI = .91, RMSEA = .04, SRMR = .06). These results indicated that the measurement instruments that we used functioned appropriately in our sample.

Regarding the first part of our main analyses, the model fit results for the LPA shown in Table 2 and the elbow plot in Figure 1 suggested that a four-profile solution fitted the data best. The four-profile solution had an entropy of .84, exceeding the cut-off of high entropy (>.80), showed improvement for AIC, BIC, and SABIC, and included profiles with meaningful theoretical value compared with the two- and three-profile solutions. Moreover, going from the four- to the five-profile solution did not result in a meaningful improvement of model fit. Therefore, the four-profile solution was chosen as the final solution given its theoretical sensibility, meaningfully sizeable profiles, and improvement on other fit indicators.

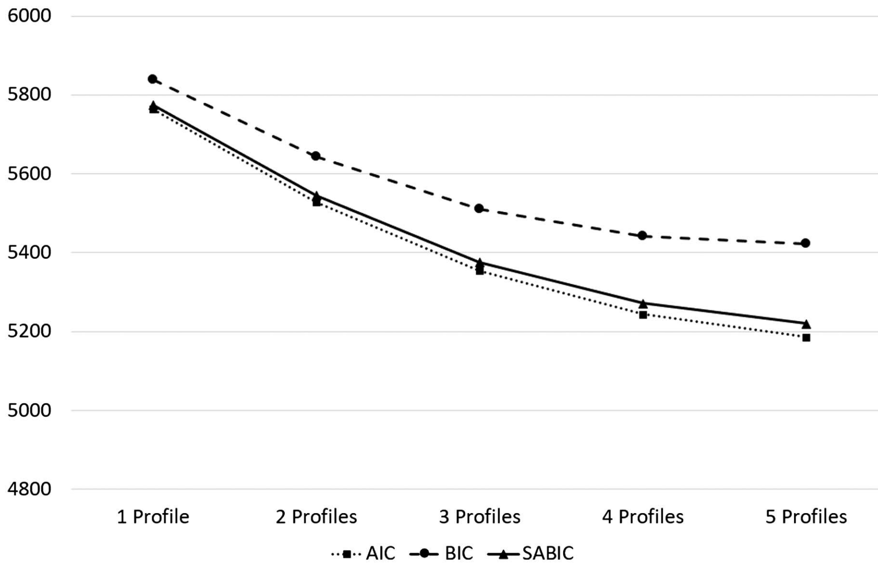
Figure 2 shows the four profiles from the final profile solution and Table 3 shows the descriptive information per profile. First, Profile A (Average Sleepers) was characterized by average scores and variability across all indicators. Second, participants in Profile B (Deep Owls) slept later (especially on Friday and Saturday nights; see supplemental Figure S1) and woke up later compared with participants in other profiles with decent sleep quality. Third, Profile C (Short Sleep Compensators) was characterized by shorter sleep duration and earlier wake time, accompanied by more variability in both dimensions. To fully understand the meaning of Profile C, supplementary analyses on the average of daily sleep duration and wake-up time were conducted. This graph is shown in the supplemental Figure S2, revealing that the average of the sleep duration was higher on Wednesday and Saturday nights, and also the lowest on Sunday night. Furthermore, on average, participants in Profile C woke up later on Thursday and Sunday mornings. These patterns showed signs of participants compensating for short sleep duration from the nights before (Sunday to Tuesday night and Thursday to Friday night) mainly by waking up later. However, after that compensation day, participants immediately shortened their sleep again. Finally, participants in Profile D (Restless Erratic Sleepers) had lower sleep quality, higher sleep fragmentation, and more variability in both dimensions. To understand the exact

Table 2
Latent Profile Enumeration Fit Statistics

Number of profiles	Number of free parameters	LL	AIC	BIC	SABIC	Smallest % of participants	Entropy
1	20	−2861.92	5763.84	5837.64	5774.22	—	—
2	31	−2732.96	5527.92	5642.32	5544.01	25.90% (77)	.84
3	42	−2635.21	5354.42	5509.42	5376.22	19.87% (59)	.83
4	53	−2569.68	5245.35	5440.94	5272.86	12.39% (37)	.84
5	64	−2529.50	5187.00	5423.18	5220.22	4.52% (13)	.86

Note. LL = log likehood; AIC = Akaike information criteria; BIC = Bayesian information criteria; SABIC = sample size–adjusted BIC.

Figure 1
Elbow Plot for AIC, BIC, and SABIC



Note. AIC = Akaike information criteria; BIC = Bayesian information criteria; SABIC = sample size–adjusted BIC.

meaning and pattern of daily scores of participants in Profile D, a supplementary analysis was conducted (see supplemental Figure S3). The graph showed that, on average, sleep fragmentation in Profile D decreased from Sunday night to Friday night and then slightly increased again on Saturday night. A different pattern for sleep quality in Profile D emerged, with sleep quality decreasing from Sunday night to Tuesday night, before increasing again until Friday night. Table 3 shows the descriptive statistics for each profile.

After the four-profile solution was chosen, the relationships between profiles, prolonged fatigue, and burnout symptoms were analyzed using direct inclusion. The profiles were similar when analyzed with the outcomes included in the model. Based on the Wald test value and the comparison between the profiles, the profiles could predict prolonged fatigue, exhaustion, mental distance, cognitive impairment, and burnout core symptoms. As shown in Table 4, Restless Erratic Sleepers tended to have higher prolonged fatigue and exhaustion, whereas Deep Owls had a higher mental distance and cognitive impairment compared with the Average Sleepers. Both Restless Erratic Sleepers and Deep Owls also showed higher overall burnout core symptoms than Average Sleepers. The R3STEP analysis with all predictor variables in Table 5 showed that workload, job control, as well as the interaction between job control and workload did not predict profile membership.

Supplementary Post Hoc Analyses

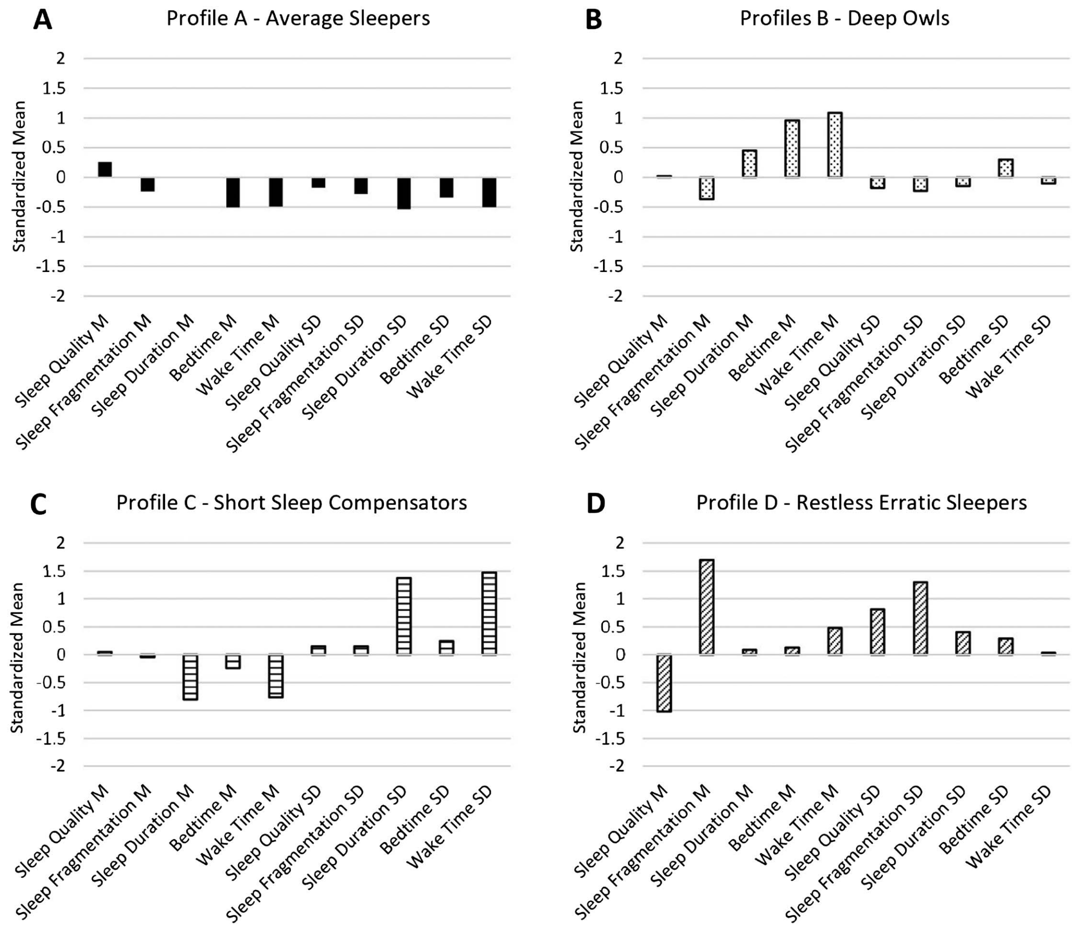
Two types of supplementary post hoc analyses were performed. First, in response to a reviewer's suggestion, we conducted a robustness check and reanalyzed the results above using only participants who completed at least three morning surveys (238 participants). The results for the profiles and predictors of the profiles were highly similar to results reported in the main results section (using the full pool of 296 participants who completed at least one morning survey). Slight differences only emerged regarding a few significance levels in the outcome results. Despite these minor differences, however, Restless Erratic Sleepers and Deep Owls still had higher prolonged fatigue and stronger burnout symptoms than the Average Sleepers. As statisticians generally advise against listwise deletion (Newman, 2014; Peugh & Enders, 2004; Tan et al., 2018; van Buuren, 2018; Wang et al., 2017), we rely on the main analyses reported in the Results section in our discussion. Nevertheless and for the sake of transparency, a detailed overview of the outcome results using only 238 participants is provided in supplemental Table S3.

Second, to highlight the added value of intraindividual variability to the meaning of sleep profiles,[2] we reran analyses without the sleep intraindividual variability dimensions (i.e., only include sleep quality, fragmentation, bedtime, wake-up time, and duration). The supplemental material contains the results of this additional analysis. Before interpreting the results, it should be emphasized that the conceptual meaning of the different analyses is profoundly different and that this post hoc LPA is estimated from less of the available information. In brief, running LPA without sleep intraindividual variability yielded more profiles (the six-profile solution was arguably the best). These profiles without intraindividual variability showed more variety in the combination of the sleep levels. However, the profiles did not reflect the compensation process of sleep as well as the original profiles that did include intraindividual variability. For instance, the full profiles reported in the main analyses (including sleep levels and variability) documented that signs of problematic sleep (e.g., short sleep duration in Short Sleep Compensators) went hand in hand with the intraindividual variability of the respective problematic dimensions (e.g., short sleep duration was combined with higher sleep duration intraindividual variability). The original results pointed to the compensation

[2] We thank a reviewer for this suggestion.

Figure 2

Standardized Means of the Sleep Indicators in the Sleep Latent Profiles



Note. Panel A: Standardized mean of sleep indicators in Average Sleepers; Panel B: Standardized mean of sleep indicators in Deep Owls; Panel C: Standardized mean of sleep indicators in Short Sleep Compensators; and Panel D: Standardized mean of sleep indicators in Restless Erratic Sleepers.

mechanisms existing as would be expected following the two-process model of sleep regulation (Borbély, 1982), which was lost in these supplementary analyses using only sleep levels. This underlines the merits of including the intraindividual variability of the sleep dimensions as it showed a possible sleep compensation process that would not be apparent otherwise.

Discussion

The present article identifies four subgroups of employees with different combinations of sleep levels and their variability throughout a week. It further reveals that these unique sleep profiles are differentially related to chronic fatigue levels. Adopting a person-centered approach, we identified four different sleep profiles that each describes unique scoring patterns of sleep dimensions. Specifically, the four identified profiles were Average Sleepers (i.e., no remarkable averages and intraindividual variability scores compared with other profiles), Deep Owls (i.e., later, bedtime and wake-up time, but average sleep quality compared with other profiles), Short Sleep Compensators (i.e., shorter, more varied sleep duration and more varied wake-up time compared with other profiles), and Restless Erratic Sleepers (i.e., lower, varied sleep quality and higher, varied sleep fragmentation compared with other profiles). Our findings also revealed that these profiles differently related to prolonged fatigue and burnout assessed 2 weeks after the weekly sleep profiles. Specifically, Restless Erratic Sleepers emerged as the most unadaptable sleep profile, followed by Deep Owls. We also sought to shed light on the role of work demands, specifically workload, job control, and the interaction of workload and job control, for profile membership. Interestingly, however, none of the aforementioned work-related variables predicted profile membership.

The identification of the four profiles shows that sleep indicators and their intraindividual variability can co-occur in meaningfully different combinations. That is, the profiles reflect the importance of considering both the average levels and the intraindividual variability of sleep dimensions across the week. This importance becomes particularly apparent when looking closely at how key sleep dimensions vary across the week within the different profiles. Specifically, the two sleep profiles characterized by higher intraindividual variability offer insight into how sleep compensation

Table 3
Descriptive Information per Latent Profile

Profile	Name	*N*	Sleep quality *M*	Sleep fragmentation *M*	Sleep duration *M*	Bedtime *M*	Wake time *M*	Sleep quality *SD*	Sleep fragmentation *SD*	Sleep duration *SD*	Bedtime *SD*	Wake time *SD*
A	Average Sleepers	132	2.98	.84	6.24	22.41 (10:25 p.m.)	5.23 (05:14 a.m.)	.34	.71	1.05	.82	.80
B	Deep Owls	77	2.90	.74	6.72	24.16 (00:10 a.m.)	7.51 (07:31 a.m.)	.34	.73	1.31	1.11	1.07
C	Short Sleep Compensators	50	2.91	1.00	5.38	22.73 (10:44 p.m.)	4.84 (04:50 a.m.)	.43	.89	2.33	1.08	2.11
D	Restless Erratic Sleepers	37	2.57	2.39	6.33	23.17 (11:10 p.m.)	6.63 (06:38 a.m.)	.60	1.39	1.69	1.10	1.16

Note. $N = 296$.

occurs in different ways. First, the Short Sleep Compensators had varying sleep duration and wake-up time, and their sleep was especially longer on Wednesday night (i.e., following three shorter nights of sleep) and Saturday night (i.e., following two shorter nights of sleep). Second, for the Restless Erratic Sleepers with varied sleep quality and fragmentation, sleep quality was better nearing the weekends. These findings offer important insights over previous studies that focus on sleep differences between weekends and weekdays (e.g., Magee et al., 2019; Smith & Lee, 2022), by showing that in at least two groups of employees sleep compensation takes place at different weekdays as well. Moreover, the dynamics of sleep differ between members of specified sleep profiles and the total population of employees in general. Clearly, both the weekly sleep profiles and the days of the week are important to consider specifically to gain proper insights into sleep and fatigue.

The identification of the four profiles shows that sleep indicators and their intraindividual variability can co-occur in meaningfully different combinations. These patterns reflect how important it is to consider not only average sleep levels but also the intraindividual variability of sleep dimensions across the week. Both the averages and the intraindividual variability of sleep meaningfully set the profiles apart and illustrate the unique sleep patterns of an employee. When looking more closely at how the key sleep dimensions varied within the week, the two sleep profiles with higher intraindividual variability also showed different patterns. Short Sleep Compensators had varying sleep duration and wake-up time, and their sleep was especially longer in the middle of the week and during the weekends. This might theoretically represent the mechanism of sleep homeostatic pressure (i.e., Process S of the sleep regulation) occurring midweek and on weekend days, in the sense that these workers' bodies demand longer sleep to compensate short sleep (Borbély, 1982). This is an important finding as previous studies have focused on sleep differences between weekends and weekdays (e.g., Magee et al., 2019; Smith & Lee, 2022), whereas important sleep compensation is clearly also reflected in weekday variation in sleep duration. For the Restless Erratic Sleepers with varied sleep quality and fragmentation, sleep quality was better nearing the weekends but poorest on Tuesday night. Interestingly, in this profile, sleep quality was particularly high on Friday night as found in previous studies (Rook & Zijlstra, 2006), but also on Sunday night, which contrasts with previous studies documenting particularly poor sleep quality for this night (Hülsheger et al., 2014; Rook & Zijlstra, 2006). These differences in findings may be explained by the fact that the present findings reflect sleep quality changes for the Restless Erratic sleepers, whereas the previous studies studied employees in general. This suggests that systematic changes in sleep across the week may vary between different groups of employees, depending on their profile. As a whole, these findings reflect how important it is to consider not only average sleep levels but also intraindividual variability in sleep across the week.

Our findings also revealed that sleep profiles were meaningfully related to prolonged fatigue and burnout. This finding adds to previous research focusing on specific sleep dimensions using a variable-centered approach and connecting sleep with well-being outcomes (e.g., Chaput et al., 2020; Litwiller et al., 2017). The unhealthiest sleep profile, the Restless Erratic Sleepers, had distinct characteristics such as poorer, slightly varied sleep quality and higher, varied sleep fragmentation. As mentioned before, the Restless Erratic Sleepers had a slightly better sleep quality nearing and during the weekend, especially on Friday and Sunday nights, which may help them to recover. However, it seems that

Table 4
Direct Inclusion Results of Distal Outcomes

Outcomes	Wald's test value	Short versus Average		Restless versus Average		Owls versus Average		Owls versus Restless		Short versus Restless		Owls versus Short	
		Est	*SE*	Est	*SE*	Est	*SE*	Est	*SE*	Est	*SE*	Est	*SE*
Prolonged fatigue[a]	9.93* (p = .019)	.14	.26	.79**	.29	.27	.23	−.52	.40	−.66	.39	.13	.34
Burnout core symptoms[b]	12.13** (p = .007)	.18	.19	.44*	.21	.35*	.15	−.08	.28	−.26	.29	.18	.23
Exhaustion[b]	8.92* (p = .03)	.11	.23	.58*	.26	.29	.22	−.30	.39	−.48	.35	.18	.33
Mental distance[b]	9.72* (p = .02)	.28	.26	.57	.37	.52*	.24	−.05	.48	−.29	.46	.24	.33
Cognitive impairment[b]	13.59** (p = .004)	.16	.23	.53	.34	.47**	.16	−.07	.39	−.37	.42	.30	.26
Emotional impairment[b]	1.01 (p = .798)	.12	.20	.11	.31	.16	.19	.05	.39	.01	.36	.04	.24
Burnout secondary symptoms[b]	12.03** (p = .007)	.10	.19	.52	.39	.39	.22	−.13	.54	−.42	.50	.29	.24

Note. Analysis was run using direct inclusion, which used listwise deletion. Short = Short Sleep Compensators; Average = Average Sleepers; Owls = Deep Owls; Restless = Restless Erratic Sleepers; Est = estimates; *SE* = standard errors.
[a] $N = 227$. [b] $N = 225$.
* $p < .05$. ** $p < .01$.

having better sleep quality on some days was not enough. Compared with the Average Sleepers with better, consistent sleep quality and lower, consistent sleep fragmentation throughout the week, Restless Erratic Sleepers have more risk of having prolonged fatigue and burnout core symptoms through the feeling of exhaustion at work. This risk still holds even though they had some favorable characteristics, such as consistent sleep timing and duration. Another unfavorable sleep profile, Deep Owls, had a later bedtime and wake-up time than other profiles. When looking closely at the bedtime per day, the Deep Owls went to bed even later during the weekend, which may indicate that they prefer going to bed later. This may reflect difficulties adjusting to the common work rhythm (Biss & Hasher, 2012) and working outside their preferred time (Nowack & van der Meer, 2018). The difficulties of matching their preferred work rhythm may explain why Deep Owls suffer mental distance and cognitive impairment as burnout core symptoms compared with the Average Sleepers.

However, the main analysis shows that sleep profiles could not explain emotional impairment and burnout secondary symptoms. This contrasts to some extent with previous findings, which associated sleep with poor emotional regulation (Barnes, 2012) and a higher risk of developing depression, cardiovascular diseases, and cancer (Irwin, 2015). Arguably, emotional impairment and burnout secondary symptoms may develop later in the burnout process. This could happen, for example, if employees stay in the undesirable profiles (i.e., Deep Owls and Restless Erratic Sleepers) for a longer time or if they experience extreme sleep problems (e.g., insomnia or severe circadian rhythm disruption due to night shifts). In such cases, the compensation that we see in our undesirable profiles might not occur and then employees develop these more severe symptoms of burnout (cf. Irwin, 2015; Walker et al., 2020). Alternatively, it is possible that the more severe cases of burnout (e.g., higher emotional impairments and secondary symptoms) were uncommon in our sample because people with such severe impairments might not be fit enough to work. This was reflected by the lower averages of burnout in the study sample compared with, for example, the Flemish sample in the original validation study of the Burnout Assessment Tool (Schaufeli, de Witte, & Desart, 2020). The averages were particularly lower for emotional impairment. This could happen because Indonesian employees may

Table 5
Three-Step Results for Antecedents (R3STEP)

Predictor	Short versus Average			Restless versus Average			Owls versus Average			Owls versus Restless			Short versus Restless			Owls versus Short		
	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*
Step 1																		
Workload	−.03	(.27)	.97	.53	(.42)	1.69	.22	(.26)	1.25	−.30	(.42)	.74	−.56	(.47)	.57	.25	(.33)	1.29
Job control	−.04	(.36)	.96	.52	(.41)	1.69	.31	(.27)	1.37	−.21	(.42)	.81	−.56	(.51)	.57	.35	(.37)	1.42
Step 2																		
Workload	−.07	(.28)	.94	.50	(.45)	1.65	.21	(.26)	1.24	−.29	(.45)	.75	−.57	(.50)	.57	.28	(.34)	1.32
Job control	−.02	(.37)	.98	.54	(.43)	1.72	.32	(.28)	1.38	−.22	(.45)	.80	−.56	(.53)	.57	.34	(.38)	1.40
Workload × Job Control	−.21	(.22)	.81	−.02	(.32)	.98	−.06	(.15)	.95	−.04	(.30)	.96	−.19	(.34)	.82	.16	(.19)	1.17

Note. $N = 296$. Short = Short Sleep Compensators; Average = Average Sleepers; Owls = Deep Owls; Restless = Restless Erratic Sleepers; Coef. = the estimate from the R3STEP multinomial regression analysis; *SE* = standard error of the coefficient; *OR* = odds ratio.

underreport emotional impairment symptoms, as Indonesian culture leans toward in-group harmony preservation, thus imposing larger restrictions on (negative) emotional outbursts at work (Panggabean et al., 2013).

Another interesting result is that the Short Sleep Compensator profile did not differentially relate to prolonged fatigue or burnout compared with other sleep profiles. Two characteristics of this profile that differentiate it from the other profiles were short sleep duration and inconsistent sleep schedule, which have been related to adverse outcomes in previous variable-centered research (Bei et al., 2016; Chaput et al., 2020; Söderström et al., 2012; van Dongen, Maislin et al., 2003; van Dongen, Rogers, & Dinges, 2003; Williams et al., 2021). The inconsistency of their sleep might show that they compensate for their short sleep on certain days, thus possibly alleviating fatigue accumulation and protecting their health in general (Chaput et al., 2020; Kubo et al., 2011). This may indicate that effective compensation for inadequate recovery is the key to avoid fatigue accumulation. Considering our findings on the backdrop of the effort–recovery model (Meijman & Mulder, 1998), employees may find it easier to compensate for inadequate sleep duration if it co-occurs with adequate sleep quality and appropriate sleep timing, so fatigue does not accumulate. This further shows the importance of not only looking at one specific aspect of sleep but also looking at it in combination with other sleep dimensions in a person-centered approach.

Aside from exploring whether different sleep combinations predicted prolonged fatigue, this study shows that workload, job control, and the interaction between the two variables did not predict profile membership. This result deviates from previous studies that link workload, job control, and its interaction with sleep (de Lange et al., 2009; Litwiller et al., 2017). Differences in findings may be explained by the fact that these previous studies considered specific sleep dimensions in isolation instead of the combination of sleep dimensions. Although they play a central role in the work stress literature, workload and job control are only two of a wider variety of work demands and resources. Other possible explanations may lie in the nonwork area, such as delaying bedtime (Kühnel et al., 2018), engaging in other behaviors or being in an environment that does not support good sleep (Shimura et al., 2020; Yang et al., 2010). Future research may therefore explore to what extent other more salient work demands and resources (e.g., hindrance stressors and social support), nonwork hindrances, and interactions between these factors could predict membership of the sleep profiles identified in the present study.

Theoretical Implications

An important theoretical implication of our study is that the profiles identified in this study show how looking at singular sleep dimensions or averaging them together in an index do not paint a complete picture. This idea aligns with previous studies on sleep profiles outside the organization sciences (e.g., Ownby et al., 2014; Smith & Lee, 2022), but including intraindividual variability of sleep dimensions in the profiles extends its relevance. Clearly, the notion of time and variation over time are essential elements to incorporate to fully understand the role of sleep in the recovery process. This notion is particularly echoed by the finding that profiles combining average weekly sleep dimension levels with intraindividual variability differentially predict some of the burnout dimensions and prolonged fatigue.

For burnout and prolonged fatigue research specifically, the present study implies that the timing of sleeping and sleep quality matters. The connection between the profile characterized by later and more variable bedtime and waking time (Deep Owls) with burnout suggests that particularly those who are living outside regular daily rhythms are at risk of developing some of the burnout core symptoms. Similar implications emerged from studies with shift workers (Åkerstedt & Wright, 2009), but as our sample consisted of workers with regular hours, it shows that this maladaptive sleep profile might put people at risk, regardless of their working times. Relatedly, sleeping shortly does not necessarily put people at risk of burnout or prolonged fatigue as previous studies have suggested (Grossi et al., 2021; van Drongelen et al., 2017). That is, when it co-occurred with good average sleep quality and early average wake-up time (Short Sleep Compensators), individuals do not seem to incur these previously suggested risks. These findings highlight the importance of adopting a person-centered (rather than variable-centered) approach in studies on burnout and prolonged fatigue in general.

Another important theoretical implication of our study is that combinations of sleep dimensions and their variability reflect the regulatory nature of sleep. That is, the profiles typically show a combined differentiation of the average levels of sleep dimensions and the variability of these same dimensions. The variability in these profiles might indicate that even though undesirably outstanding scores on dimensions on average tend to automatically be compensated on specific days. In that sense, variability can be viewed as a sign of the body trying to repair employees' sleep deficits rather than a sleep problem. Arguably, this idea also has implications for the accumulation of fatigue; the recovery process seems to do its work via sleep relatively automatically, thus delaying the fatigue accumulation process as mentioned in the effort–recovery model (Meijman & Mulder, 1998). Consequently, symptoms related to chronic fatigue could be more difficult to incur than is generally assumed, and it might not be fatigue build-up that causes people to suffer from prolonged fatigue and burnout but rather a lack of adequate compensation via sleep. In this study, compensations for short sleep seem to work for participants to lessen recovery inadequacy mentioned in the effort–recovery model (Meijman & Mulder, 1998), but it is not the case for poor sleep quality and inappropriate sleep timing. However, studies with longer measurement periods incorporating intraindividual variability are needed to get definitive answers on the exact nature and process of how symptoms related to chronic fatigue can happen (Fischer et al., 2021). As previously discussed, the differences in sleep dynamics between the profiles and their differences with previous research (e.g., Hülsheger et al., 2014; Rook & Zijlstra, 2006) suggest that future studies on the temporal dynamics of sleep should consider using person-centered approaches. Future studies can use growth mixture modeling to explore whether different subgroups reflect different types of daily sleep quality or duration changes across 1 week.

Practical Implications

The present study yields important practical implications. First, our findings demonstrate the importance of sleep profiles for health and well-being and present a fine-grained understanding of what "healthy profiles" look like. Drawing on previous research (Barnes et al., 2017; Skeldon et al., 2017) and given the implications of sleep and fatigue on work functioning (Litwiller et al., 2017), organizations can facilitate employees in maintaining healthy sleeping profiles. That is, organizations can identify which group of employees is especially at risk due to unhealthy sleep patterns (i.e., Restless Erratic Sleepers and Deep Owls). Employees in these two groups can be encouraged to minimize light in the evening and maximize having natural light in the morning (Skeldon et al., 2017) and be offered to have individual intervention in case of recurring sleep problems (Barnes et al., 2017). Finally, one way of helping employees achieve a healthier sleep profile might reside in offering catch-up opportunities. In alignment with previous studies, the profiles demonstrate the adaptive nature of catching up with sleep (Kubo et al., 2011). As such, sleeping breaks at work might offset some of the negative effects of an unhealthy sleep profile (Milner & Cote, 2009), but future research should be conducted to get more definitive answers on this point.

Limitations and Future Directions

Like every study, the present study includes some limitations to take into account when interpreting the evidence. A potential limitation relates to the generalizability of the findings, as the study was conducted with only Indonesian employees. Sleep patterns of Indonesians might be different compared with other countries, such as earlier waking time (Daban & Goh, 2019). Furthermore, Indonesia only has two seasons and does not have large differences in daylight time all year round due to its position near the equator. This is different from countries with seasonal effects, affecting sleep dimensions such as wake times and duration (Mattingly et al., 2021). Although this feature of our study offers an important contribution to and enrichment of the literature that has, to date, predominantly focused on Western cultures, it remains to be tested to what extent the profiles extend to other (e.g., Western) populations.

Second, although we used time-separated measurement—burnout and prolonged fatigue 2 weeks after and work characteristics the week before measuring sleep variables, our study design does not offer insights into causal relations between sleep profiles and burnout and prolonged fatigue. Future studies may therefore employ a cross-lagged model to understand the direction of the relationship between profiles and burnout and prolonged fatigue.

Last, we relied on self-report measures, which is a potential source of bias (Podsakoff et al., 2003). To reduce the possibility of common method bias, we used time-separated measurement of the sleep dimensions, predictors, and outcomes. Specifically, work characteristics were measured in the baseline survey, sleep dimensions in the diary part, and fatigue and burnout on average 15 days after the end of the diary part. However, future studies could consider using objective measurements of sleep to obtain multisource data.

Our findings showcase the merits of incorporating indicators of sleep variability alongside sleep levels into a person-centered approach. Future research may explore to what extent including measures of intraindividual variability may also enrich profiles of recovery activities and experiences that have, to date, only considered trait or state levels (e.g., Bennett et al., 2016; Chawla et al., 2020). For instance, employees who feel consistently relaxed in the evening may have a lower risk of chronic symptoms of fatigue than employees with similar average levels but high variability in evening relaxation. Studying this may address the question of whether recovery experiences are best kept stable or whether one can compensate for poor recovery experiences on one evening with high recovery experiences on the next.

Conclusion

The present study adds to the recovery and sleep literature by adopting a person-centered approach, integrating information on levels and variability of key sleep dimensions. By doing so, we identified four sleep profiles among employees: "Average Sleepers," "Deep Owls," "Short Sleep Compensators," and "Restless Erratic Sleepers." Importantly, employees with a "Deep Owls" and "Restless Erratic Sleeper" profile seem especially vulnerable to prolonged fatigue and some burnout symptoms. In contrast to expectations, workload, job control, and their interaction did not predict profile membership. Taken together, our findings highlight how a person-centered approach that integrates information on sleep levels and variability provides novel insights into the role of sleep for chronic fatigue and burnout. It also has important practical implications as it reveals subgroups of employees who are at particular risk and may require specific attention.

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Received December 21, 2022
Revision received April 14, 2023
Accepted April 26, 2023 ■