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### ► **To cite this version:**

Nicolas Gillet, Céline Diaz, Tiphaine Huyghebaert-Zouaghi. A longitudinal person-centered investigation of the multidimensional nature of deviant work behaviors. *Journal of Managerial Psychology*, 2026, <10.1108/jmp-12-2024-0939>. <hal-05546367>

**HAL Id: hal-05546367**

**<https://hal.science/hal-05546367v1>**

Submitted on 10 Mar 2026

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*Running head:* Longitudinal Deviant Behaviors Profiles

## **A Longitudinal Person-Centered Investigation of the Multidimensional Nature of Deviant Work Behaviors**

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### **This is the prepublication version of the following manuscript:**

Gillet, N., Diaz, C., & Huyghebaert-Zouaghi, T. (in press). A Longitudinal Person-Centered Investigation of the Multidimensional Nature of Deviant Work Behaviors. *Journal of Managerial Psychology*.

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### **Abstract**

*Purpose.* This person-centered investigation seeks to further understand the nature of deviant work behaviors profiles including presenteeism, abuse against others, soldiering, and cyberslacking. We also aimed to investigate the longitudinal stability of these profiles and of their relations with a series of predictors (i.e., availability expectations through information and communication technology, challenge demands, and hindrance demands).

*Design/methodology/approach.* A sample of 415 employees completed the same set of measures twice across a three-month period.

*Findings.* Our results revealed four profiles: Involved, High Presenteeism, Low Presenteeism, and Problematic. These profiles were highly stable over time. Availability expectations through information and communication technology, challenge demands, and hindrance demands displayed distinctive patterns of association with profile membership.

*Originality.* The person-centered approach adopted in this study highlights the importance of this joint consideration of various deviant work behaviors to better understand the combinations of these behaviors and thus provide a more realistic reflection of the reality.

*Keywords.* Counterproductive work behaviors; procrastination; latent transition analyses; job demands; hindrance and challenge demands; information and communication technology.

Given their harmful effects on organizational functioning and performance (Holland *et al.*, 2016), deviant work behaviors have recently received a high level of scientific attention (Fouquereau *et al.*, 2019). In the current investigation, we chose to consider four key deviant work behaviors (i.e., presenteeism, abuse against others, and two components of procrastination at work: Soldiering and cyberslacking) that have been shown to reflect employees' ill-being and to be key predictors of decreased organizational performance (Holland *et al.*, 2016; Miraglia and Johns, 2016). For instance, Gillet *et al.* (2023) have demonstrated that presenteeism was more strongly related to work performance and job satisfaction than other prevalent forms of workplace deviance such as absenteeism and counterproductive work behaviors. Procrastination at work has also been found to be a strong predictor of organizational deviance (Jahanzeb *et al.*, 2023), while abuse against others is quite prevalent and comes with substantial costs (Fox *et al.*, 2012). A comprehensive understanding of these deviant behaviors may thus offer key practical insights to devise evidence-based interventions and counteract performance declines.

Moreover, we chose to focus on these behaviors because they are conceptually aligned and theoretically relevant to the person-centered approach. Indeed, presenteeism, procrastination, and abuse against others can be framed as overt behaviors reflecting psychological mechanisms related to self-regulation, personal agency, and motivation (Holland *et al.*, 2016; Metin *et al.*, 2020; Miraglia and Johns, 2016) making them particularly relevant for a joint person-centered approach. In contrast, other deviant behaviors such as gossip, withdrawal, or sabotage reflect more covert behaviors that often involve more complex group processes or passive/indirect expressions that extend beyond the scope of individual-level analysis (Fox *et al.*, 2012). Therefore, by concentrating on presenteeism, procrastination, and abusive behaviors, this study may provide critical insight into individual behavioral profiles focused on direct, overt behaviors.

More specifically, presenteeism implies that employees attend work when their health condition prevents them from working properly (Miraglia and Johns, 2016). Abuse against others refers to physically or psychologically harmful behaviors towards other people in the work setting (Holland *et al.*, 2016). Soldiering is a form of procrastination at work that involves doing non-related work activities without wanting to do harm (Metin *et al.*, 2020). Cyberslacking is an online form of procrastination at work wherein employees give the impression of working on their devices while engaging in personal online activities (e.g., online shopping, social media, gaming; Metin *et al.*, 2020).

Although these four deviant work behaviors have generally been considered using an additive approach, their effects have never been conceptualized as independent or simply additive. Indeed, they are suggested to coexist, to vary independently from one another, and to interact with one another (Gillet *et al.*, 2023; Metin *et al.*, 2020). Unfortunately, prior investigations have either ignored the distinctiveness of these behaviors by computing them into a single global indicator of deviant work behaviors or have considered such behaviors in isolation or in pairs only (e.g., Fouquereau *et al.*, 2019). This broad brush or piecemeal consideration is unlikely to provide a complete picture of the complex reality of deviant work behaviors that need to be considered through a finer-grained approach. Interestingly, person-centered studies have recently begun to examine various combinations of work behaviors within different profiles of employees (Gillet *et al.*, 2023; Klotz *et al.*, 2018). In doing so, these studies have paved the way for a better understanding of how employees behave at work, while shedding light on the behavioral configurations that are most prevalent among employees and helping to identify levers to prevent the most detrimental profiles for employees' and organizations' functioning.

Yet, these person-centered studies either focused solely on positive behaviors (i.e., organizational citizenship behaviors; Klotz *et al.*, 2018) or on a mix of positive and negative

behaviors (Gillet *et al.*, 2023), thus leaving unknown the nature of deviant work behaviors profiles (DWBP; i.e., negative behaviors only). Although Gillet *et al.* (2023) did consider some deviant behaviors, they only considered a limited set, leaving unknown how prevalent behaviors such as abuse against others or procrastination at work (Holland *et al.*, 2016; Metin *et al.*, 2020) interplay with other deviant behaviors. The first contribution of this study is thus to extend knowledge on the nature of DWBP by examining how deviant behaviors that were not previously examined (i.e., soldiering, cyberslacking, and abuse against others) combine with presenteeism to characterize subpopulations of workers. Moreover, prior person-centered research on work behaviors examined a limited set of predictors of profile membership (i.e., Gillet *et al.*, 2023: social support and emotional dissonance; Klotz *et al.*, 2018: prosocial values, impression management, and organizational concern). As such, little is known about the predictors of DWBP and other factors that may hinder or contribute to their development remain to be documented. The second contribution of this study is thus to expand the nomological network associated with employees' behavioral combinations by examining theoretically relevant predictors (supervisors' availability expectations, challenge and hindrance demands) that were not previously examined.

An additional limitation of the emerging person-centered studies of work behaviors is that they have relied on cross-sectional (Gillet *et al.*, 2023) or on prospective (Klotz *et al.*, 2018) designs that do not allow to examine profile stability over time. Yet, deviant work behaviors are known to evolve (Henderson and Matthews, 2024). Therefore, further studies are needed to determine whether similar profiles are identified over time or whether employees' membership into these profiles remains stable. The third contribution of this study is thus to offer a robust examination of the stability of behavioral profiles and of their relations with predictors across three months.

The novelty of the present research thus lies in these contributions intended to address gaps in existing person-centered research on behavioral combinations. In doing so, the present research could offer meaningful theoretical and practical insights into the dynamic nature of employees' deviant work behaviors in modern work contexts.

#### ***A Person-Centered Approach of Deviant Work Behaviors***

In prior studies, Klotz *et al.* (2018) identified five profiles of organizational citizenship behaviors (i.e., sportsmanship, altruism, conscientiousness, courtesy, and civic virtue), while Gillet *et al.* (2023) also identified five profiles of work behaviors (i.e., performance, presenteeism, absenteeism, and counterproductive work behaviors). These profiles are described in the online supplements. Yet, these results can only be considered preliminary, given the diversity of the behaviors considered and the limited number of investigations. To extend knowledge on the nature of deviant work behaviors combinations, we relied on a theoretical approach linked to the characteristics and psychological mechanisms underlying these DWBP. More specifically, to understand the nature of DWBP, we used several theoretical perspectives that inform our rationale on each profile indicator, namely conservation of resources theory (COR; Hobfoll, 1989), social exchange theory (SET; Conway and Coyle-Shapiro, 2012), and self-determination theory (SDT; Ryan, 2023).

A first scenario characterizes ***Involved*** employees, displaying low presenteeism, abuse, soldiering, and cyberslacking. These employees work in a context that satisfies their psychological needs and promotes their autonomous motivation (Ryan, 2023). In other words, they feel empowered, free to act, and interested in their work, which gives them the necessary resources for optimal functioning and self-regulation (Hobfoll, 1989). As a result, they do not engage in deviant behaviors, as they have the psychological resources for meaningful task engagement and do not wish to disrupt their fulfilling work environment (Conway and Coyle-Shapiro, 2012).

The second scenario characterizes ***Problematic*** employees, displaying high presenteeism,

abuse, soldiering, and cyberslacking. These employees work in a context that thwarts or neglects their psychological needs, leading them to develop controlled forms of motivation, characterized by external pressures (Ryan, 2023). These employees may feel that their organization is not honoring its side of the psychological contract and feel that their work investment is not sufficiently recognized and valued (Conway and Coyle-Shapiro, 2012). This situation may drain their psychological resources (Hobfoll, 1989). To preserve their remaining resources, these employees may be tempted to put less effort into their work and instead engage in non-work-related activities (Metin *et al.*, 2020). They may also engage in abusive behavior towards others who may be perceived as representative of the organization, as a way to reciprocate and restore justice (Qin and Zhang, 2022).

The third scenario characterizes *Withdrawn* employees, displaying high levels of presenteeism, soldiering, and cyberslacking, but low levels of abuse. These workers' needs for autonomy and competence may be unfulfilled, while their need for relatedness remains satisfied (Huyghebaert-Zouaghi *et al.*, 2023). These employees might not understand the rationale for task engagement and may drain their resources trying to make sense of this situation (Hobfoll, 1989). They might thus show up at work but do other things to find interest while trying to restore their resources. These employees may also feel that their efforts are not recognized, which they may perceive as an unfair situation. In order to restore fairness, their willingness to contribute actively to the success of the organization may decrease and their levels of presenteeism and procrastination at work may increase (Qin and Zhang, 2022). However, these employees are not tempted to engage in abusive behaviors against others because they maintain an affective bond with their peers (Huyghebaert-Zouaghi *et al.*, 2023).

These theoretical scenarios have only been partially supported by the results obtained by Gillet *et al.* (2023) and have not been confirmed in other studies to date. They should thus not be regarded as the only possible combinations, and profiles with different characteristics might be identified. Since we have only limited information on the characteristics of these profiles and the number of potential scenarios, it would be premature to formulate clear-cut hypotheses. Instead, we hope that the scenarios presented here, combined with the findings of empirical investigations (see the online supplements), may serve as a basis for further theoretical developments.

*Hypothesis 1.* We will identify at least three profiles reflecting the three theoretical scenarios (*Involved*, *Problematic*, and *Withdrawn*).

### **A Longitudinal Person-Centered Approach**

Prior studies on work behaviors profiles have been cross-sectional, with one exception (Klotz *et al.*, 2018). However, Klotz *et al.* (2018) relied on a prospective design and did not measure work behaviors repeatedly, so the over-time stability of profiles could not be examined. Yet, evidence of within-sample (i.e., whether the same set of profiles will be estimated over time) and within-person (i.e., whether employees will retain the same profile over time) stability is a key requirement for the development of person-centered interventions (Gillet *et al.*, 2024; Huyghebaert-Zouaghi *et al.*, 2022). Indeed, to support the value of person-centered interventions, profiles must be found to reflect more than ephemeral phenomena (Huyghebaert-Zouaghi *et al.*, 2022). Other variable-centered longitudinal investigations have typically shown that presenteeism, procrastination at work, and abuse against others (Hall *et al.*, 2019; Matthews and Ritter, 2016) were moderately to highly stable over time. Behavioral inertia may explain these levels of stability as employees tend to adopt the same behavioral patterns in their work environment due to habit and identity consistence, without actively adjusting or changing, and feeling satisfied in such resource-preserving situations (Stoner *et al.*, 2011). Furthermore, employees who perceive a high degree of stability in their employment contract may find no interest in changing their work behaviors

and disrupt an otherwise stable and comfortable situation (Chambel *et al.*, 2016). Therefore, we expected behavioral combinations to remain stable over a three-month period. In relation to past investigations (Gillet *et al.*, 2024; Huyghebaert-Zouaghi *et al.*, 2022), we expected this timeframe to be appropriate because it is not limited to daily fluctuations (Rivkin *et al.*, 2022), while remaining short enough to ensure a proper measurement of stability under conditions that can generally be expected to be reasonably stable for most employees (Idris *et al.*, 2023). In line with all of these considerations, we suggest that:

*Hypothesis 2.* We will confirm the within-sample stability of the profiles, which will display a moderate to high level of within-person stability.

### ***Job Demands as Predictors of Profile Membership***

In the present study, we wanted to examine how different job demands could predict membership into DWBP. More specifically, we looked into supervisors' availability expectations, challenge demands (i.e., skill discretion, time pressure, and decision authority), and hindrance demands (i.e., interruptions, work overload, and poor supervision). These predictors were chosen in view of their widely demonstrated effects on the deviant work behaviors considered in this research (e.g., Fouquereau *et al.*, 2019; Miraglia and Johns, 2016). In addition to the previously mentioned theoretical perspectives (i.e., SDT, SET, and COR theory), we relied on the job demands-resources model (Bakker *et al.*, 2023) as an overarching framework to understand the associations between these job demands and DWBP.

Employees facing high availability expectations or hindrance demands may remain in a constant state of activation, forcing them to tap into their personal resources to properly cope with these situations, and may thus experience resource depletion (Hobfoll, 1989). Because of the continuous psychological and/or physical effort and poor recovery experiences induced by availability expectations and hindrance demands, they may suffer from a health-impairment process (Bakker *et al.*, 2023), and may thus reduce effort (e.g., high levels of soldiering and cyberslacking; Metin *et al.*, 2020) and display high levels of presenteeism (Idris *et al.*, 2023) to protect themselves in the face of this resource loss spiral and preserve their remaining resources. Indeed, strain is associated with withdrawal behaviors and lower commitment (e.g., presenteeism, procrastination at work; French *et al.*, 2019). Employees may also engage in abuse against those pressuring them via availability expectations (Ryan, 2023), or against those who are protected from hindrance demands as a way to restore justice. For instance, employees may take out their anger and frustration on coworkers who do not face such expectations or hindrance demands, to reciprocate for this unfair treatment (Qin and Zhang, 2022).

*Hypothesis 3.* Higher levels of availability expectations and hindrance demands will predict a lower likelihood of membership into the profiles with the lowest levels of deviant work behaviors (e.g., *Involved* profile) in comparison to the other profiles.

LePine *et al.* (2005) highlighted that not all job demands are necessarily detrimental and differentiated hindrances (demands that obstruct personal growth and goal attainment) from challenges (demands that promote learning, development, and fulfillment). According to the job demands-resources model (Bakker *et al.*, 2023), workers may perceive their job demands as challenging when they possess sufficient personal and professional resources to successfully cope with and gain from these job demands. This positive resource gain spiral (Hobfoll, 1989) may thus be associated with low levels of deviant work behaviors, as employees find opportunities for growth in these challenges (Ryan, 2023) and want to positively reciprocate for this stimulating work environment, while having the necessary energy to be fully involved in their work tasks (Hobfoll, 1989).

*Hypothesis 4.* Higher levels of challenge demands will predict a higher likelihood of membership into the profiles with the lowest levels of deviant work behaviors (e.g., *Involved*

profile) in comparison to the other profiles.

## Method

### *Participants and Procedure*

Participants were invited to complete an online questionnaire twice over a period of three months via the *Prolific Academic* crowdsourcing platform. The sample included 415 participants (60.2% females) at Time 1 (T1), and 327 participants (60.0% females) at Time 2 (T2). Participants lived and worked in the UK (75.1%) or USA (24.9%), and 70.8% held a university degree. They had a mean age of 40.19 years ( $SD = 10.22$ ) and a mean tenure in their position of 6.95 years ( $SD = 6.45$ ). A majority held a permanent (98.3%) full-time (85.5%) position. Participants mainly worked in the private sector (55.2%). Before accessing the survey, participants were told that they could withdraw from the project at any time, and that participation was confidential and voluntary. At each data collection time, participants received £2.25 for their participation.

### *Measures*

All measures are detailed in Table 1.

## Results

### *Preliminary Analyses*

We relied on preliminary factor analyses to verify the psychometric properties of all multi-item measures. The specification of these analyses and their results are reported in Tables S1 to S4 of the online supplements (factor structure, composite reliability, and measurement invariance over time). All of our main analyses were based on factor scores extracted from these preliminary models in standardized units ( $SD = 1$ ;  $M = 0$ ) and specified as invariant over time to ensure their comparability over time. Factor scores also have the advantage of preserving the nature of the measurement model from which they are extracted (factor structure and invariance) and of incorporating a partial correction for unreliability (Skrondal and Laake, 2001). Correlations are reported in Table S5 of the online supplements.

### *Main Analyses*

The model fit indicators associated with the time-specific latent profile analyses are reported and interpreted in the online supplements (also see Table S6 and Figures S1 and S2). At both time points, these indicators failed to support any specific solution. However, the elbow plots revealed a first plateau between two and three profiles, and a second plateau between four and five profiles at both time points. Thus, we more carefully examined solutions including three to five profiles. These solutions were very similar over time and revealed that additional profiles brought value up to four profiles, at both time points. More precisely, if we consider the solution illustrated in Figure 1, Profiles 1, 3, and 4 were already present in the three-profile solution, and Profile 2 was added in the four-profile solution. However, the addition of a fifth profile led to the arbitrary division of existing profiles into spurious profiles representing less than 1% of the sample, with no added theoretical contribution, since two profiles had a similar shape but only slightly different levels. Therefore, the four-profile solution was selected at both time points.

The model fit indicators associated with the longitudinal models are reported in Table S7 of the online supplements which also provide details on longitudinal tests of profile similarity. The model of *distributional* similarity was selected as our final model and retained for interpretation. This model was associated with a high classification accuracy (see Table S8: 86.2% to 93.3% at T1; 87.7% to 95.2% at T2), consistent with a high entropy of .797. The results from this final four-profile model are graphically displayed in Figure 1 and reported in more details in Tables S8 and S9 of the online supplements.

Membership into Profiles 1 (*Involved*: Stability of 78.6%), 2 (*High Presenteeism*: Stability of 85.1%), 3 (*Low Presenteeism*: Stability of 81.8%), and 4 (*Problematic*: Stability of 78.1%) was stable over time (see Table S10 of the online supplements). The results detailed in the

online supplements (also see Table S7) revealed a lack of relations between the demographic controls (sex, age, level of education, tenure in the current position, contract, working time, sector, and country) and the profiles at both time points. Thus, demographic controls were not retained for subsequent analyses.

In contrast, the results reported in Table S7 were consistent with the generalizability of our theoretical predictors' associations with the profiles over time, supporting the *predictive* similarity of the solution. Results from this model are reported in Table S11 of the online supplements and revealed that availability expectations predicted a decreased likelihood of membership into the *Low Presenteeism* (3) profile relative to the *Involved* (1), *High Presenteeism* (2), and *Problematic* (4) profiles. Challenge demands predicted an increased likelihood of membership into the *Involved* (1) and *High Presenteeism* (2) profiles relative to the *Low Presenteeism* (3) and *Problematic* (4) profiles. Contrastingly, hindrance demands predicted an increased likelihood of membership into the *Low Presenteeism* (3) and *Problematic* (4) profiles relative to the *Involved* (1) and *High Presenteeism* (2) profiles.

### Discussion

This study built upon prior research on behavioral combinations (Gillet *et al.*, 2023; Klotz *et al.*, 2018) to further document the longitudinal nature of DWBP and thus provide a more realistic reflection of the reality.

#### ***Deviant Work Behaviors Profiles (DWBP)***

This study helps address the scarcity of person-centered investigations considering how distinct types of deviant work behaviors are experienced in combination by employees (Gillet *et al.*, 2023). Extending past research, the profiles identified confirmed the key role of presenteeism in profile definition (Miraglia and Johns, 2016), emphasizing how critical it is to consider this work behavior when seeking to fully grasp deviant work behaviors.

The four distinct DWBP identified in this study are partially consistent with Hypothesis 1. Indeed, as expected, we identified an *Involved* profile characterized by very low to moderately low levels of presenteeism, abuse against others, soldiering, and cyberslacking, as well as a *Problematic* profile, displaying high levels across all deviant work behaviors. This generalization of results across a limited body of emerging studies on work behaviors (Gillet *et al.*, 2023; Klotz *et al.*, 2018) suggests that similar profiles can be expected to be identified across work contexts and cultural settings. Although we had no a priori reason to expect results to be impacted by the cultural characteristics of the samples, this diversity is critical as person-centered evidence is built from an accumulation of studies (Gillet *et al.*, 2023). It is indeed critical to differentiate the common set of profiles that occur in most contexts from the more specific profiles that only emerge in specific contexts or samples. Although we provided evidence of generalizability for these two profiles, more studies are still needed to confirm that the profiles identified in this study may generalize to other deviant work behaviors (e.g., drug and alcohol use, gendered counterproductive work behaviors, production deviance) and to other occupations and countries (e.g., collectivistic).

The other two profiles were not as consistent with our proposed theoretical scenarios. We did identify a profile with high levels of presenteeism (*High Presenteeism* profile), as proposed in the *Withdrawn* scenario, but employees within this profile rather reported average (instead of low) levels of abuse, and low (instead of high) levels of soldiering and cyberslacking. These results thus highlight that employees can attend work even if their health condition prevents them from working properly, without necessarily procrastinating. This *High Presenteeism* profile reinforces the unique nature of presenteeism (Miraglia and Johns, 2016), as this behavior may come to dominate the actions of at least one profile of employees. We also identified a *Low Presenteeism* profile characterized by moderately high levels of abuse against others, and, perhaps most importantly, dominated by high levels of procrastination, together with low levels of presenteeism. This result reinforces the idea that

above average levels of presenteeism and procrastination are not necessarily aligned and can be mutually exclusive, except when combined in an overall deviant profile such as the *Problematic* profile.

Altogether, our study concurs with the suggestions to consider multiple, and conceptually distinct work behaviors (e.g., Gillet *et al.*, 2023; Klotz *et al.*, 2018), as it indicates that there is added value in differentiating among presenteeism, abuse against others, soldiering, and cyberslacking, which may converge with one another at high (e.g., *Problematic* profile) or low (e.g., *Involved* profile) levels, but also differ from one another (e.g., *High Presenteeism* profile), within one profile. This conclusion is aligned with previous reports revealing only moderate correlations between these deviant work behaviors (e.g., Metin *et al.*, 2020).

### ***Longitudinal Stability of DWBP***

This study contributes to prior research by providing the first evidence of stability of DWBP. Supporting their generalizability, all profiles were replicated over a three-month period, indicating that these profiles capture core mechanisms involved in employees' behavioral functioning. Regarding profiles' within-person stability, membership was highly stable over a three-month period. Consistent with theoretical mechanisms such as behavioral inertia, perceived contract stability, or identity maintenance (Chambel *et al.*, 2016; Stoner *et al.*, 2011), these stability rates match previous reports showing that deviant work behaviors appear moderately to highly stable over comparable time intervals (Hall *et al.*, 2019; Matthews and Ritter, 2016). These stability rates thus support the value of profile-based interventions, suggesting that the current set of DWBP neither capture rigid conditions, nor entirely ephemeral tendencies (Huyghebaert-Zouaghi *et al.*, 2022).

Membership into the *Involved* and *Problematic* profiles was the least stable over time. These results suggest that it might be difficult to maintain low or high levels of all deviant work behaviors over time (even for a period as short as three months). Indeed, it may be hard to sustain low levels of deviant behaviors as the workplace is an imperfect world and all employees may experience resource loss, lack of motivation, or unfair treatment every so often, thus occasionally relying on deviant behaviors to preserve their resources, engage in pleasurable activities, or restore justice (Coyle and Shapiro, 2012; Hobfoll, 1989; Ryan, 2023). In contrast, it may also be difficult for employees to maintain high levels of deviant work behaviors in a society where hard work is valued and working environments shape attendance behaviors (Gillet *et al.*, 2017).

Interestingly, when they transitioned to a new profile at T2, members of the *Problematic* profile transitioned to the *Low Presenteeism* profile. For members of the *High Presenteeism* profile at T1, transitions were directed toward the *Involved* profile at T2. High levels of presenteeism may thus tend to decline over time for some employees. These changes could be due to organizational changes, coping resource replenishment, or role adjustment between T1 and T2. For instance, organizations might have promoted the legitimacy of using sick leave when necessary or flexible work arrangements allowing employees to better preserve their resources (e.g., Idris *et al.*, 2023).

### ***Predictors of DWBP***

Availability expectations predicted a decreased likelihood of membership into the *Low Presenteeism* profile relative to the three other profiles. First, this *Low Presenteeism* profile differed from the *High Presenteeism* and *Problematic* profiles which were characterized by higher levels of presenteeism. These results thus suggest that availability expectations may be associated with higher levels of presenteeism. Indeed, when the boundaries between personal and professional lives are blurred, resource regulation is impaired as employees cannot recover effectively (Bakker *et al.*, 2023). Because of their constant activation, their available resources are progressively depleted and employees experience ill-being (Hobfoll, 1989). As a result, employees' presenteeism increases when they still attend work despite their health

condition, possibly to avoid their colleagues having too much work as a result of their absence (Miraglia and Johns, 2016). Second, although the *Involved* profile also showed low levels of presenteeism, employees within this profile also displayed lower levels of procrastination and abuse against others. Availability expectations thus seem to be associated with lower levels of abuse against others, soldiering, and cyberslacking at least when employees display, at the same time, low levels of presenteeism. When such employees experience work-related intrusions into their personal life, they may experience anxiety, gradually lose interest in their work, and disengage from their interpersonal relations and from their work tasks (Ryan, 2023).

Availability expectations also predicted an increased likelihood of membership into the *Problematic* profile relative to the *Low Presenteeism* profile (characterized by slightly lower levels of abuse and procrastination but especially by lower levels of presenteeism), but not to the *Involved* profile (characterized by lower levels across all dimensions). As suggested above, availability expectations could essentially affect presenteeism, but future research will be needed to better understand the mechanisms and boundary conditions of these associations. For instance, *Involved* employees might be more active copers (de Rijk *et al.*, 1998) inclined to use job control as a means to attenuate the negative effects of availability expectations, using discretion in how and when they accomplish their tasks, despite external pressures.

In contrast, and as expected, hindrance demands predicted a decreased likelihood of membership into the *Involved* profile relative to the *Low Presenteeism* and *Problematic* profiles, while challenge demands displayed the opposite pattern of associations with these profiles. These results confirm that hindrance demands are incompatible with low levels of deviant work behaviors because they are associated with negative emotions and a resource loss spiral that may lead to deviant work behaviors (Hobfoll, 1989; Metin *et al.*, 2020). These results also demonstrate that employees need to deal with challenging and stimulating work situations in order to be fully invested in it and not exhibit deviant work behaviors (Hobfoll, 1989). More generally, consistent with prior research (e.g., Gillet *et al.*, 2024; LePine *et al.*, 2005), the present findings emphasize the need to clearly distinguish between different types of job demands that may have diametrically opposite effects.

Interestingly, challenge demands also predicted an increased likelihood of membership into the *High Presenteeism* profile relative to the *Low Presenteeism* and *Problematic* profiles. In other words, challenge demands primarily facilitate the development of high levels of presenteeism coupled with average to low levels of abuse against others and procrastination. Indeed, employees may position work at the core of their life priorities and invest more time and energy in their work role, which can become an important source of life fulfillment. This makes it difficult for them to distance themselves from their work even when they have very little energy left and that their condition does not allow them to be effective. Indeed, these employees may experience negative emotions (e.g., frustration) when unable to work as much as they want. This result is also consistent with past studies showing that challenge demands were positively related to overcommitment (e.g., workaholism, obsessive passion; Gillet *et al.*, 2017) and suggests double-edged sword effects of challenge demands (LePine *et al.*, 2005).

In addition, hindrance demands predicted an increased likelihood of membership into the *Low Presenteeism* and *Problematic* profiles relative to the *High Presenteeism* profile. These results first suggest that hindrance demands are so draining that they may lead employees to take leaves (*Low Presenteeism* profile) in order to restore lost resources and to cope with this overly demanding work environment (Bakker *et al.*, 2023). Second, these results also suggest a cumulative resource loss cycle (Hobfoll, 1989) in the face of hindrance demands, which translates into high levels of all deviant work behaviors in the *Problematic* profile as

employees try to avoid further resource loss (i.e., procrastination and presenteeism) and lack the resources to properly regulate their negative emotions (e.g., abuse against others; Hobfoll, 1989; Metin *et al.*, 2020), all while reciprocating for their exposure to hindering job demands.

### ***Limitations and Suggestions for Future Research***

In this research, we relied solely on self-report questionnaires, which implies that social desirability biases may have played a role in our results. Furthermore, the inter-item reliability of scores obtained on various subscales was suboptimal, suggesting that further research with other measures may be required to confirm our findings. Nevertheless, these limitations do not call into question the validity of our results, as we relied on factor scores in our main analyses. These factor scores provide a relatively strong (even if partial) control for unreliability, thereby limiting concerns about low reliability. Future research could use different sources of data (e.g., supervisor's procrastination ratings, objective records of sick leave or turnover) to increase objectivity and widen the scope of our findings. Second, this study only involved workers who lived and worked in the USA or the UK, the majority of whom were private-sector and university-educated white collars. Additional studies will be needed to test the replicability of the current findings to a variety of occupational roles, work settings, and cultures to reinforce our results' external validity.

Third, we measured the stability of DWBP over a period of three months during which no specific transition, intervention, or systematic change occurred for most participants. Stability would likely be smaller – making it easier to detect transitions and their predictors – if longer time intervals (e.g., six months, one year), or intervals encompassing interventions, changes, or transitions, were considered. Fourth, our longitudinal design with two data collections makes it impossible to achieve a complete understanding of the shape and dynamics of deviant work behaviors. More extensive longitudinal designs including at least three time points and growth mixture modeling are thus needed. Fifth, the methodological and analytical design used in this study precludes conclusions regarding the directionality, causality, or associations between predictors and DWBP, which had to be assumed based on theory and are likely to be reciprocal in nature. These questions would need to be more thoroughly examined in future studies relying on methodological designs allowing for tests of directionality or causality (e.g., job crafting interventions aiming at changing challenge and hindrance demands; Knight *et al.*, 2021).

Finally, we only considered a narrow set of predictors and future research could investigate how other job (e.g., employment contract, colleagues and supervisor ostracism) and personal (e.g., workaholism, proactive personality) characteristics are linked and interact to predict profile membership (e.g., Gillet *et al.*, 2017; Jahanzeb *et al.*, 2023). Likewise, negative (e.g., customer complaints, attention-related cognitive errors) and positive (e.g., work productivity, customer loyalty) outcomes of deviant work behaviors combinations could be examined to better understand the implications of DWBP (e.g., Rivkin *et al.*, 2022).

### ***Conclusions and Implications for Practice***

Based on the present findings, managers and organizations who wish to limit presenteeism, abuse against others, and procrastination among their employees have a vested interest in ensuring that employees are not continuously exposed to hindrance demands as they facilitate the development of a *Problematic* profile. In contrast, they could encourage the development of challenge demands that are strongly linked to membership in the *Involved* profile. However, caution is warranted as challenge demands may also be associated with overcommitment and higher levels of presenteeism. Nevertheless, the adverse effects of challenging job demands tend to disappear when hindering job demands are low (Gillet *et al.*, 2024). Joint actions to reduce hindering job demands and increase challenging job demands can thus be considered. It is noteworthy that such interventions require limited investment relative to the costs associated with an increase in such misbehaviors in modern work

contexts (Holland *et al.*, 2016). From an intervention perspective, high levels of hindrance demands could be reduced by facilitating the development of work environments that support employees' psychological needs and well-being (Huyghebaert-Zouaghi *et al.*, 2023). Job crafting interventions seeking to help employees craft their job could also be useful in decreasing hindering job demands and increasing challenging job demands in the short and medium term (Seppälä *et al.*, 2023).

Our results also point to the detrimental implications of supervisors' availability expectations for DWBP. To target these expectations, organizations would gain in promoting a culture that is respectful of work-life balance and of employees' right to disconnect. Segmentation norms (e.g., not sending emails or messages outside of working hours; Huyghebaert-Zouaghi *et al.*, 2022) could be introduced right from supervisors' and employees' hiring process and onboarding, together with clear disconnection rules and recommendations (e.g., not processing emails or messages received outside of working hours). To get to the root of the problem, organizations could also implement actions to limit work outside of regular hours, such as shutting down servers and email systems in the evenings and on weekends or displaying pop-up messages to encourage supervisors to disconnect when they are logged in outside working hours. Frequent internal surveys on perceived availability expectations could also allow for a better understanding of employees' perceptions and enable the implementation of tailored interventions.

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**Table 1***Measures*

Construct	Authors	Number of items	Sample item	Response scale	$\alpha_{T1}$	$\alpha_{T2}$
Challenge demands	French <i>et al.</i> (2019)	3	How often does your work demand a high level of skill or expertise?	5-point	.63	.65
Hindrance demands	French <i>et al.</i> (2019)	3	How often do you feel that you are ignored or not taken seriously by your boss?	5-point	.63	.54
Availability expectations	Derks <i>et al.</i> (2015)	4	I feel that I have to respond to messages from my supervisor immediately during leisure time.	5-point	.91	.94
Presenteeism	Koopman <i>et al.</i> (2002)	6	During the past month, I was able to focus on achieving my work goals despite my health problems.	5-point	.92	.90
Abuse	Holland <i>et al.</i> (2016)	4	During the past month, I started an argument with someone at work (e.g., supervisor, coworker).	7-point	.61	.70
Soldiering	Metin <i>et al.</i> (2020)	8	I delay before starting on work I have to do.	7-point	.92	.92
Cyberslacking	Metin <i>et al.</i> (2020)	4	I read news online during working hours.	7-point	.83	.86

*Note.*  $\alpha$ : Cronbach's alpha; T1: Time 1; T2: Time 2. Omega coefficients are reported in Tables S2 and S4 of the online supplements.

**Online Supplements for:  
A Longitudinal Person-Centered Investigation of the Multidimensional Nature of  
Deviant Work Behaviors**

**Prior Person-Centered Investigations**

Despite the lack of prior investigations on employees' work behaviors profiles, some research has highlighted the value of a person-centered approach, demonstrating that work behaviors cannot be apprehended independently. For instance, in their first study, Klotz et al. (2018) identified five profiles of organizational citizenship behaviors characterized by different levels of sportsmanship, altruism, conscientiousness, courtesy, and civic virtue: 1) *Prosocial citizens* profile with the highest levels of all five organizational citizenship behaviors; 2) *Disengaged* profile with the lowest levels of all five types of organizational citizenship behaviors; 3) *Contributors* profile with relatively high levels of all types of organizational citizenship behaviors; 4) *Moderates* profile with slightly below-average levels of all organizational citizenship behaviors except conscientiousness; and 5) *Specialists* profile with relatively high levels of civic virtue and altruism, average levels of sportsmanship and conscientiousness, and low levels of courtesy. Klotz et al. (2018) replicated four of these five profiles in a second study.

In a study more closely related to the present research, given the variables considered (i.e., performance, presenteeism, absenteeism, and counterproductive work behaviors), Gillet et al. (2023) identified five profiles of work behaviors: 1) *Deviant-Presenteeism* profile (high counterproductive work behaviors, moderately high presenteeism, and moderately low performance and absenteeism); 2) *Withdrawn (Presenteeism)* profile (low counterproductive work behaviors, moderately low absenteeism and performance, and high presenteeism); 3) *Average (Maladaptive)* profile (moderately high presenteeism, average counterproductive work behaviors and absenteeism, and moderately low performance); 4) *Problematic* profile (very high absenteeism, high presenteeism, moderately high counterproductive work behaviors, and low performance); and 5) *Involved* profile (low presenteeism, moderately low counterproductive work behaviors and absenteeism, and moderately high performance).

**Preliminary Measurement Models**

**Analyses**

Given our reliance on complex longitudinal models involving multiple multidimensional constructs, we conducted preliminary analyses separately for the deviant work behaviors (presenteeism, abuse, cyberslacking, and soldiering) and predictors (availability expectations through information and communication technology: ICT, challenge demands, and hindrance demands). These preliminary analyses relied on Mplus 8.9 (Muthén & Muthén, 2023) and on the mean and variance adjusted weight least square (WLSMV) estimator. We also relied on full information maximum likelihood (FIML; Enders, 2010) to deal with missing data, allowing us to save factor scores including no missing data. Factor scores are partially corrected for random measurement error (Skrondal & Laake, 2001) and maintain the properties of the measurement model (e.g., invariance) better than scale scores (Morin et al., 2016a). As the chi-square test of exact fit ( $\chi^2$ ) is oversensitive to minor misspecifications, omitted variables, and sample size (e.g., Marsh et al., 2005), models were assessed and compared using sample-size independent fit indices (Hu & Bentler, 1999): The Tucker-Lewis index (TLI), comparative fit index (CFI), and root mean square error of approximation (RMSEA) coupled with its 90% confidence interval. Values above .90 are acceptable for TLI and CFI, although values above .95 are recommended. Values below .08 are acceptable for the RMSEA, although values below .05 are preferred. Likewise, tests of measurement invariance relied on changes in fit indices (Chen, 2007; Cheung & Rensvold, 2002). A  $\Delta$ CFI/TLI of .010 or less and a  $\Delta$ RMSEA of .015 or less between a model and the previous model indicates that the invariance is supported. We also report composite reliability

coefficients (omega:  $\omega$ ) calculated from the standardized parameters (McDonald, 1970):

$$\omega = \frac{(\sum |\lambda_i|)^2}{[(\sum |\lambda_i|)^2 + \sum \delta_i]}$$

In this formula,  $|\lambda_i|$  reflects the standardized factor loadings, and  $\delta_i$ , the item uniquenesses.

For deviant work behaviors, we relied on a confirmatory factor analysis (CFA) model with three correlated factors (presenteeism, abuse, cyberslacking, and soldiering) at both Time 1 (T1) and Time 2 (T2). All items were used to assess their a priori factor, with no cross-loading or correlated uniqueness. Similarly, the model used to represent the multi-item predictors included three factors (availability expectations through ICT, challenge demands, and hindrance demands) defined solely by their a priori items, with no cross-loading or correlated uniqueness. These three factors were also allowed to freely correlate with one another.

We then proceeded to tests of measurement invariance for each of these solutions over time (Millsap, 2011): (i) configural invariance; (ii) weak (loadings) invariance; (iii) strong (loadings and intercepts) invariance; (iv) strict (loadings, intercepts/thresholds, and uniquenesses) invariance; (v) invariance of the latent variance-covariance matrix; and (vi) latent means invariance.

## Results

The model fit of all deviant work behaviors solutions are presented in Table S1, and confirmed the adequacy of the CFA model underlying the deviant work behaviors, as well as the configural, weak, strong, strict, latent variances-covariances, and latent means invariance of this solution over time. For our main analyses, factor scores were saved from this final model (latent means invariance), for which parameter estimates are reported in Table S2. These results revealed that presenteeism ( $\lambda = .872$  to  $.961$ ,  $\omega = .969$ ), abuse ( $\lambda = .715$  to  $.867$ ,  $\omega = .871$ ), soldiering ( $\lambda = .704$  to  $.889$ ,  $\omega = .941$ ), and cyberslacking ( $\lambda = .748$  to  $.903$ ,  $\omega = .888$ ) were all well-defined by satisfactory factor loadings and composite reliability coefficients.

The model fit of the models including the predictors is presented in Table S3 and confirms the adequacy of these measurement models, as well as their configural, weak, strong, strict, latent variances-covariances, and latent means invariance over time. For our main analyses, factor scores were saved from this final model (latent means invariance), for which parameter estimates are reported in Table S4. The factors representing availability expectations through ICT ( $\lambda = .817$  to  $.945$ ,  $\omega = .942$ ), challenge demands ( $\lambda = .532$  to  $.858$ ,  $\omega = .700$ ), and hindrance demands ( $\lambda = .382$  to  $.916$ ,  $\omega = .699$ ) were well-defined by satisfactory factor loadings and composite reliability coefficients. Correlations among all variables are shown in Table S5.

## Main Analyses

### Latent Profile Analyses

Our main analyses relied on full information maximum likelihood estimation (Enders, 2010) to handle missing data. This approach allowed us to estimate all models using the responses from all participants who completed at least one time point ( $n = 415$ ), rather than relying on the problematic listwise deletion of participants who did not complete both time points ( $n = 88$ ). Time-specific latent profile analytic models including one to eight profiles were first estimated while allowing the means of the four deviant work behaviors to be estimated freely across profiles (Morin & Litalien, 2019). These models relied on 5000 sets of random start values, 1000 iterations, and 200 final optimizations (Hipp & Bauer, 2006), while the latter longitudinal models relied on 10000 random starts, 1000 iterations, and 500 final optimizations.

Identifying the optimal number of profiles to retain is a complex decision that needs to be taken while considering multiple sources of information, including (Marsh et al., 2009;

McLachlan & Peel, 2000): (a) whether each added profile brings a meaningful contribution to the solution; (b) whether each added profile is theoretically consistent; (c) whether each added profile results in a statistically proper solution (e.g., convergence, lack of negative variance estimates); and (d) a variety of statistical indicators to guide this decision. For these last criteria, lower values on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Consistent AIC (CAIC), and sample-size Adjusted BIC (ABIC) indicate better fitting models. Moreover, a statistically significant Bootstrap Likelihood Ratio Test (BLRT) and adjusted Lo, Mendell, and Rubin's (2001) Likelihood Ratio Test (aLMR) both support a model relative to one including fewer profiles. However, statistical research has shown that the BIC, CAIC, ABIC, and BLRT, but not the AIC and aLMR, were efficient at guiding the identification of the optimal number of latent profiles (Diallo et al., 2016, 2017). For this reason, we only report the AIC and aLMR to ensure complete disclosure, and will not use these indices for model comparison. In addition, these tests all present a strong sample size dependency (Marsh et al., 2009) and thus often fail to converge on a specific solution. When this happens, scores on the AIC, BIC, CAIC, and ABIC, as a function of the number of profiles, should be graphically presented in the form of an elbow plot, where the observation of a plateau in the decrease in these values helps to pinpoint the optimal solution (Morin et al., 2011). In practice (e.g., Meyer & Morin, 2016; Morin & Litalien, 2019), the statistical indicators are considered first to help pinpoint a range of acceptable solutions, which are then examined to eliminate those that are statistically improper, before being contrasted in terms of meaningfulness and theoretical conformity. Lastly, we also report an indicator of classification accuracy, the entropy, which should not be used to select the optimal number of profiles (Lubke & Muthén, 2007).

### **Longitudinal Tests of Profile Similarity**

As long as the same number of profiles is identified at both time points, the two time-specific solutions can be integrated into a single longitudinal latent profile model. This model can then be used to conduct longitudinal tests of within-sample profile similarity (Morin & Litalien, 2017; Morin et al., 2016b). These tests are realized in a sequential manner, starting by the verification of whether the same number of profiles is identified over time. Both time-specific solutions are then integrated into a single model of *configural* similarity to which equality constraints are then imposed in sequence on the within-profile means (*structural* similarity), variances (*dispersion* similarity), and size (*distributional* similarity). Model comparisons rely on the BIC, CAIC, and ABIC, and profile similarity is supported when two of these indices decrease in a model relative to the previous one in the sequence (Morin et al., 2016b).

Following from the model of *configural* similarity, the model of *structural* similarity resulted in lower BIC, CAIC, and ABIC values, and was thus retained. The next models of *dispersion* and *distributional* similarity were also supported by the data. The model of *distributional* similarity was selected as our final model and retained for interpretation. In this model, Profile 1 displayed very low levels of soldiering, low levels of presenteeism and cyberslacking, and moderately low levels of abuse. This Involved profile characterized 14.93% of the participants. Profile 2 represented participants reporting high levels of presenteeism, average levels of abuse, and low levels soldiering and cyberslacking. This High Presenteeism profile corresponded to 26.46% of the participants. Profile 3 represented participants reporting low levels of presenteeism, moderately high levels of abuse, and high levels of soldiering and cyberslacking. This Low Presenteeism profile corresponded to 35.16% of the participants. Finally, Profile 4 represented participants reporting high levels across all dimensions. This Problematic profile corresponded to 23.45% of the participants.

### **Latent Transition Analyses**

A latent transition specification (allowing T1 profiles to predict T2 profiles) was then

added to the most similar longitudinal solution to investigate within-person stability and transitions (Collins & Lanza, 2010). This solution and all subsequent analyses were estimated via the manual three-step approach (Asparouhov & Muthén, 2014; Morin & Litalien, 2017). Results revealed that 21.4% of the members of the *Involved* profile at T1 transitioned to the *High Presenteeism* profile at T2. For members of the *High Presenteeism* profile at T1, transitions involved the *Involved* (10.6%) and *Low Presenteeism* (4.3%) profiles at T2. For members of the *Low Presenteeism* profile at T1, transitions involved the *Problematic* (16.0%) and *High Presenteeism* (2.3%) profiles at T2. Finally, when they transitioned to a new profile at T2, members of the *Problematic* profile transitioned to the *Low Presenteeism* (21.9%) profile at T2.

### **Predictors of Profile Membership**

We initially investigated the need to incorporate demographics (sex, age, level of education, tenure in the current position, contract, working time, sector, and country) as controlled variables in subsequent analyses. Indeed, past studies have shown that these variables are significantly related to deviant work behaviors. For instance, men are more exposed to presenteeism than women (Sheridan, 2004). Similarly, meta-analytic evidence showed a significant effect of age on presenteeism (Miraglia & Johns, 2016). Nguyen et al. (2013) have also demonstrated that employment status and duration were significantly linked to procrastination at work. In line with these findings, men and younger employees might have a higher likelihood of membership into the profiles characterized by high levels of presenteeism (e.g., *Problematic*).

These variables were first incorporated to the solution through a multinomial logistic regression link function, and four alternative models were contrasted. The first, null effects, model assumed no associations between these demographics and the profiles. In the second model, the effects of these variables were freely estimated at both time points, and the predictions involving the T2 profiles were allowed to differ across all T1 profiles (i.e., reflecting the effect of these variables on specific transitions). In a third model, these predictions only varied as a function of time. In the last model (*predictive similarity*), these associations were constrained to equality over time. Relations between the theoretical predictors (i.e., availability expectations through ICT, challenge demands, and hindrance demands) and profile membership were then assessed using the same sequence.

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**Table S1***Goodness-of-Fit Statistics for the Estimated Models (Deviant Work Behaviors)*

Description	$\chi^2$ (df)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (df)	$\Delta$ CFI	$\Delta$ TLI	$\Delta$ RMSEA
<i>Deviant Work Behaviors</i>										
Time 1	966.863 (203)*	.965	.960	.095	[.089; .101]	-	-	-	-	-
Time 2	962.960 (203)*	.959	.953	.107	[.100; .114]	-	-	-	-	-
<i>Deviant Work Behaviors: Longitudinal Invariance</i>										
M1. Configural invariance	2391.101 (852)*	.956	.951	.066	[.063; .069]	-	-	-	-	-
M2. Weak invariance	2410.774 (870)*	.956	.952	.065	[.062; .068]	M1	15.261 (18)	.000	+0.001	-.001
M3. Strong invariance	2479.645 (949)*	.957	.957	.062	[.059; .065]	M2	103.306 (79)*	+0.001	+0.005	-.003
M4. Strict invariance	2507.164 (971)*	.956	.957	.062	[.059; .065]	M3	77.355 (22)*	-.001	.000	.000
M5. Variance-covariance invariance	2392.220 (981)*	.960	.961	.059	[.056; .062]	M4	16.664 (10)	+0.004	+0.004	-.003
M6. Latent means invariance	2388.944 (985)*	.960	.962	.059	[.056; .062]	M5	10.141 (4)*	.000	+0.001	.000

*Note.* \*  $p < .01$ ;  $\chi^2$ : Scaled chi-square test of exact fit; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval; CM: Comparison model; and  $\Delta$ : Change in fit relative to the CM.

**Table S2**

*Standardized Factor Loadings ( $\lambda$ ) and Uniquenesses ( $\delta$ ) for the M6 Solution (Longitudinal Latent Means Invariance Deviant Work Behaviors)*

Items	Presenteeism $\lambda$	Abuse $\lambda$	Soldiering $\lambda$	Cyberslacking $\lambda$	$\delta$
Presenteeism					
Item 1	.930				.135
Item 2	.890				.207
Item 3	.939				.118
Item 4	.872				.240
Item 5	.961				.077
Item 6	.901				.189
Abuse					
Item 1		.715			.489
Item 2		.737			.457
Item 3		.846			.285
Item 4		.867			.248
Soldiering					
Item 1			.787		.380
Item 2			.889		.209
Item 3			.845		.285
Item 4			.825		.320
Item 5			.808		.346
Item 6			.817		.332
Item 7			.704		.505
Item 8			.848		.281
Cyberslacking					
Item 1				.786	.383
Item 2				.903	.185
Item 3				.748	.441
Item 4				.817	.333
$\omega$	.969	.871	.941	.888	

*Note.*  $\lambda$ : Factor loading;  $\delta$ : Item uniqueness;  $\omega$ : Omega coefficient of composite reliability; all parameters are significant ( $p < .01$ ).

**Table S3***Goodness-of-Fit Statistics for the Estimated Models (Predictors)*

Description	$\chi^2$ (df)	CFI	TLI	RMSEA	90% CI	CM	$\Delta\chi^2$ (df)	$\Delta$ CFI	$\Delta$ TLI	$\Delta$ RMSEA
<i>Predictors</i>										
Time 1	230.236 (32)*	.971	.959	.122	[.108; .137]	-	-	-	-	-
Time 2	212.479 (32)*	.971	.960	.131	[.115; .148]	-	-	-	-	-
<i>Predictors: Longitudinal Invariance</i>										
M1. Configural invariance	663.569 (145)*	.963	.952	.093	[.086; .100]	-	-	-	-	-
M2. Weak invariance	672.954 (152)*	.963	.954	.091	[.084; .098]	M1	4.282 (7)	.000	+0.002	-0.002
M3. Strong invariance	723.992 (179)*	.961	.959	.086	[.079; .092]	M2	49.871 (27)*	-0.002	+0.005	-0.005
M4. Strict invariance	728.787 (189)*	.962	.962	.083	[.077; .089]	M3	15.930 (10)	+0.001	+0.003	-0.003
M5. Variance-covariance invariance	693.558 (195)*	.965	.966	.078	[.072; .085]	M4	11.135 (6)	+0.003	+0.004	-0.005
M6. Latent means invariance	684.853 (198)*	.966	.967	.077	[.071; .083]	M5	1.163 (3)	+0.001	+0.001	-0.001

*Note.* \*  $p < .05$ ;  $\chi^2$ : Scaled chi-square test of exact fit; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval; CM: Comparison model; and  $\Delta$ : Change in fit relative to the CM.

**Table S4**

*Standardized Factor Loadings ( $\lambda$ ) and Uniquenesses ( $\delta$ ) for the M6 Solution (Longitudinal Latent Means Invariance Predictors)*

Items	Supervisor expectations $\lambda$	Challenge demands $\lambda$	Hindrance demands $\lambda$	$\delta$
Supervisor expectations				
Item 1	.945			.107
Item 2	.903			.185
Item 3	.911			.170
Item 4	.817			.332
Challenge demands				
Item 1		.858		.264
Item 2		.532		.717
Item 3		.572		.672
Hindrance demands				
Item 1			.916	.161
Item 2			.637	.595
Item 3			.382	.854
$\omega$	.942	.700	.699	

*Note.*  $\lambda$ : Factor loading;  $\delta$ : Item uniqueness;  $\omega$ : Omega coefficient of composite reliability; all parameters are significant ( $p < .01$ ).

**Table S5**  
*Correlations between Variables*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Sex	-														
2. Age	.120 <sup>*</sup>	-													
3. Working time	-.251 <sup>**</sup>	.081	-												
4. Sector	-.182 <sup>**</sup>	.041	.084	-											
5. Country	.156 <sup>*</sup>	-.063	-.158 <sup>**</sup>	-.169 <sup>**</sup>	-										
6. Education	.024	-.127 <sup>**</sup>	-.098 <sup>*</sup>	.088	.014	-									
7. Tenure	.072	.381 <sup>**</sup>	.120 <sup>*</sup>	.085	-.011	-.177 <sup>**</sup>	-								
8. Contract	.008	-.001	.056	-.004	-.030	.044	-.092	-							
9. Presenteeism (T1)†	-.051	.039	.058	.044	-.015	-.042	.084	-.048	-						
10. Abuse (T1)†	.063	-.077	-.052	-.054	.008	-.073	-.097 <sup>^</sup>	-.004	.197 <sup>**</sup>	-					
11. Soldiering (T1)†	-.109 <sup>*</sup>	-.234 <sup>**</sup>	.033	.088	-.081	.152 <sup>**</sup>	-.194 <sup>**</sup>	.025	.121 <sup>*</sup>	.382 <sup>**</sup>	-				
12. Cyberslacking (T1)†	-.055	-.345 <sup>**</sup>	-.083	.018	-.064	.087	-.196 <sup>**</sup>	.036	-.001	.266 <sup>**</sup>	.648 <sup>**</sup>	-			
13. Availability expectations (T1)†	.022	-.036	.027	-.140 <sup>**</sup>	.094	-.007	.062	-.017	.123 <sup>^</sup>	.257 <sup>**</sup>	.055	-.055	-		
14. Challenge demands (T1)†	-.107 <sup>*</sup>	.026	-.028	-.011	-.155 <sup>**</sup>	.017	.018	.036	.131 <sup>**</sup>	.145 <sup>**</sup>	.009	-.159 <sup>**</sup>	.252 <sup>**</sup>	-	
15. Hindrance demands (T1)†	-.104 <sup>*</sup>	-.035	.039	.012	-.156 <sup>**</sup>	.025	.001	.003	.139 <sup>**</sup>	.292 <sup>**</sup>	.186 <sup>**</sup>	-.053	.477 <sup>**</sup>	.820 <sup>**</sup>	-
16. Presenteeism (T2)†	-.081	.068	.118 <sup>^</sup>	.085	.005	-.038	.105 <sup>^</sup>	-.040	.693 <sup>**</sup>	.065	.048	-.084	.132 <sup>**</sup>	.140 <sup>**</sup>	.129 <sup>**</sup>
17. Abuse (T2)†	.060	-.046	-.037	-.039	.012	-.088	-.085	-.002	.184 <sup>**</sup>	.986 <sup>**</sup>	.316 <sup>**</sup>	.163 <sup>**</sup>	.268 <sup>**</sup>	.167 <sup>**</sup>	.306 <sup>**</sup>
18. Soldiering (T2)†	-.133 <sup>*</sup>	-.242 <sup>**</sup>	.053	.116 <sup>*</sup>	-.103 <sup>*</sup>	.139 <sup>**</sup>	-.222 <sup>**</sup>	.032	.106 <sup>*</sup>	.394 <sup>**</sup>	.932 <sup>**</sup>	.654 <sup>**</sup>	.023	.005	.177 <sup>**</sup>
19. Cyberslacking (T2)†	-.068	-.350 <sup>**</sup>	-.075	.056	-.066	.066	-.216 <sup>**</sup>	.056	-.035	.273 <sup>**</sup>	.584 <sup>**</sup>	.942 <sup>**</sup>	-.046	-.151 <sup>**</sup>	-.045
20. Availability expectations (T2)†	-.016	-.017	.025	-.143 <sup>**</sup>	.103 <sup>**</sup>	-.053	.065	-.036	.112 <sup>*</sup>	.221 <sup>**</sup>	.029	-.080	.898 <sup>**</sup>	.257 <sup>**</sup>	.433 <sup>**</sup>
21. Challenge demands (T2)†	-.085	.045	-.041	-.011	-.129 <sup>**</sup>	-.001	.034	.059	.117 <sup>*</sup>	.095	-.065	-.197 <sup>**</sup>	.231 <sup>**</sup>	.951 <sup>**</sup>	.687 <sup>**</sup>
22. Hindrance demands (T2)†	-.131 <sup>**</sup>	.003	.014	.020	-.144 <sup>**</sup>	.001	.011	.012	.141 <sup>**</sup>	.250 <sup>**</sup>	.129 <sup>**</sup>	-.099 <sup>^</sup>	.384 <sup>**</sup>	.888 <sup>**</sup>	.932 <sup>**</sup>

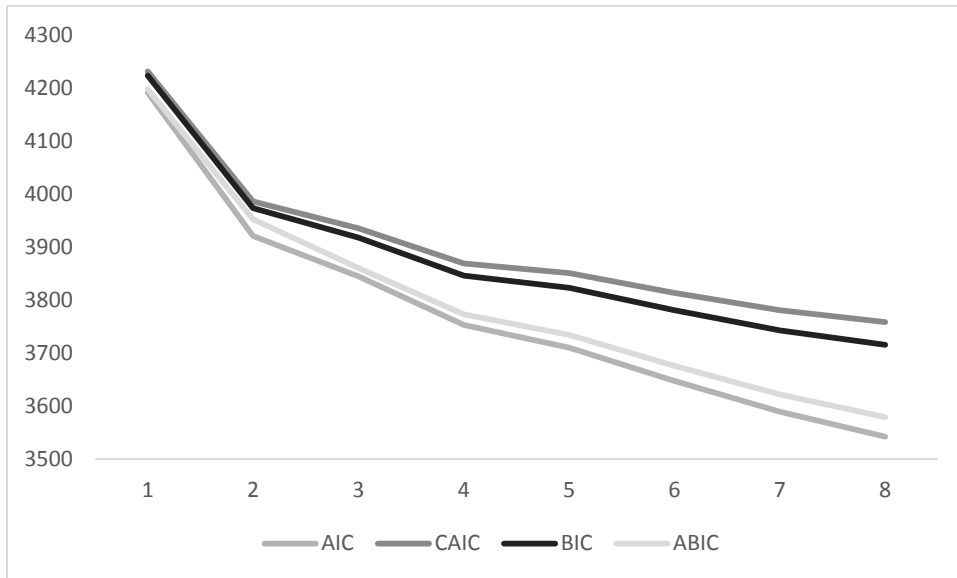
	16	17	18	19	20	21	22
16. Presenteeism (T2)†	-						
17. Abuse (T2)†	.123 <sup>*</sup>	-					
18. Soldiering (T2)†	.045	.355 <sup>**</sup>	-				
19. Cyberslacking (T2)†	-.051	.214 <sup>**</sup>	.674 <sup>**</sup>	-			
20. Availability expectations (T2)†	.120 <sup>*</sup>	.236 <sup>**</sup>	.016	-.066	-		
21. Challenge demands (T2)†	.158 <sup>**</sup>	.119 <sup>*</sup>	-.074	-.194 <sup>**</sup>	.261 <sup>**</sup>	-	
22. Hindrance demands (T2)†	.155 <sup>**</sup>	.268 <sup>**</sup>	.121 <sup>*</sup>	-.095	.441 <sup>**</sup>	.827 <sup>**</sup>	-

Note. \*  $p < .05$ ; \*\*  $p < .01$ ; † variables estimated from factor scores with a mean of 0 and a standard deviation of 1; sex was coded 0 for women and 1 for men; working time was coded 0 for employed full-time and 1 for employed part-time; sector was coded 0 for private sector and 1 for public sector; country was coded 0 for UK and 1 for USA; education was coded 0 for non-university students and 1 for students with a university degree; contract was coded 0 for permanent contract and 1 for temporary contract; and work type was coded 0 for onsite workers and 1 for remote workers.

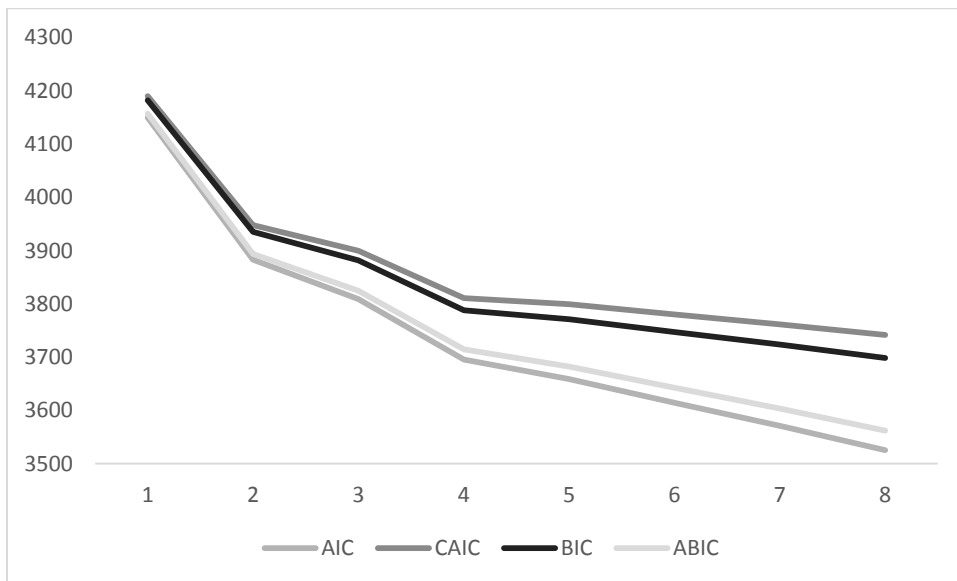
**Table S6***Results from the Latent Profile Analysis Models at Times 1 and 2*

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
<i>Time 1</i>										
1 Profile	-2087.756	8	.927	4191.513	4231.739	4223.739	4198.353	Na	Na	Na
2 Profiles	-1947.613	13	1.133	3921.226	3986.593	3973.593	3952.341	.948	< .001	< .001
3 Profiles	-1904.619	18	1.059	3845.237	3935.746	3917.746	3860.628	.875	< .001	< .001
4 Profiles	-1853.637	23	1.248	3753.275	3868.925	3845.925	3772.940	.833	.007	< .001
5 Profiles	-1827.246	28	1.282	3710.493	3851.285	3823.285	3734.434	.841	.178	< .001
6 Profiles	-1790.850	33	1.280	3647.701	3813.634	3780.634	3675.917	.917	.167	< .001
7 Profiles	-1756.843	38	1.277	3589.687	3780.762	3742.762	3622.178	.928	.143	< .001
8 Profiles	-1728.114	43	1.304	3542.228	3758.444	3715.444	3578.994	.912	.141	< .001
<i>Time 2</i>										
1 Profile	-2067.134	8	.927	4150.267	4190.493	4182.493	4157.107	Na	Na	Na
2 Profiles	-1928.493	13	1.132	3882.987	3948.354	3935.354	3894.102	.947	< .001	< .001
3 Profiles	-1886.673	18	1.070	3809.346	3899.855	3881.855	3824.737	.866	< .001	< .001
4 Profiles	-1824.649	23	1.236	3695.297	3810.948	3787.948	3714.963	.838	.002	< .001
5 Profiles	-1801.326	28	1.206	3658.652	3799.444	3771.444	3682.593	.841	.076	< .001
6 Profiles	-1774.318	33	1.400	3614.635	3780.569	3747.569	3642.851	.907	.517	< .001
7 Profiles	-1747.452	38	1.501	3570.903	3761.978	3723.978	3603.395	.879	.495	< .001
8 Profiles	-1719.716	43	1.529	3525.432	3741.648	3698.648	3562.199	.896	.459	< .001

*Note.* LL: Model loglikelihood; #fp: Number of free parameters; scaling: Scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaike information criteria; CAIC: Constant AIC; BIC: Bayesian information criteria; ABIC: Sample size adjusted BIC; aLMR: Adjusted Lo-Mendel-Rubin likelihood ratio test; and BLRT: Bootstrap likelihood ratio test.



**Figure S1**  
 Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 1



**Figure S2**  
 Elbow Plot of the Value of the Information Criteria for Solutions Including Different Numbers of Latent Profiles at Time 2

**Table S7***Results from the Time-Specific and Longitudinal Models*

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
<i>Final Latent Profile Analyses</i>								
Time 1	-1853.637	23	1.248	3753.275	3868.925	3845.925	3772.940	.833
Time 2	-1824.649	23	1.236	3695.297	3810.948	3787.948	3714.963	.838
<i>Longitudinal Latent Profile Analyses</i>								
Configural Similarity	-3688.387	46	1.299	7468.774	7700.075	7654.075	7508.106	.817
Structural Similarity	-3705.063	30	1.870	7470.127	7620.975	7590.975	7495.778	.797
Dispersion Similarity	-3705.106	26	2.039	7462.212	7592.947	7566.947	7484.443	.797
Distributional Similarity	-3705.274	23	2.246	7456.547	7572.198	7549.198	7476.213	.797
<i>Predictive Similarity: Demographics</i>								
Null Effects Model	-2992.698	59	1.350	6103.396	6400.065	6341.065	6153.843	.886
Profile-Specific Free Relations with Predictors	-2909.677	203	.971	6225.355	7246.096	7043.096	6398.927	.903
Free Relations with Predictors	-2942.103	107	1.211	6098.206	6636.231	6529.231	6189.694	.904
Equal Relations with Predictors	-2951.284	83	1.248	6068.569	6485.916	6402.916	6139.536	.893
<i>Predictive Similarity: Predictors</i>								
Null Effects Model	-2197.217	42	1.113	4478.435	4689.622	4647.622	4514.346	.886
Profile-Specific Free Relations with Predictors	-2148.137	96	.733	4488.273	4970.988	4874.988	4570.357	.901
Free Relations with Predictors	-2162.744	60	1.014	4445.488	4747.185	4687.185	4496.790	.901
Equal Relations with Predictors	-2169.742	51	1.097	4441.485	4697.927	4646.927	4485.091	.890

*Note.* LL: Model loglikelihood; #fp: Number of free parameters; Scaling: Scaling correction factor associated with robust maximum likelihood estimates; AIC: Akaike information criteria; CAIC: Constant AIC; BIC: Bayesian information criteria; ABIC: Sample size adjusted BIC.

**Table S8***Detailed Parameter Estimates from the Final LPA Solution (Distributional Similarity)*

	Profile 1 Mean [CI]	Profile 2 Mean [CI]	Profile 3 Mean [CI]	Profile 4 Mean [CI]
Presenteeism	-.687 [-.754, -.620]	.752 [.652, .851]	-.661 [-.693, -.629]	.745 [.648, .841]
Abuse	-.268 [-.562, .025]	-.011 [-.171, .148]	.198 [.090, .307]	.571 [.161, .981]
Soldiering	-1.100 [-1.592, -.607]	-.515 [-1.005, -.026]	.407 [.163, .651]	.737 [.254, 1.221]
Cyberslacking	-.841 [-1.225, -.457]	-.513 [-.987, -.039]	.438 [.187, .690]	.617 [.207, 1.027]

*Note.* CI = 95% confidence interval; the profile indicators are estimated from factor scores with a mean of 0 and a standard deviation of 1; Profile 1: *Involved*; Profile 2: *High Presenteeism*; Profile 3: *Low Presenteeism*; and Profile 4: *Problematic*.

**Table S9**

*Classification Accuracy: Average Probability of Membership into Each Latent Profile (Column) as a Function of the Most Likely Profile Membership (Row)*

	Profile 1	Profile 2	Profile 3	Profile 4
<i>Time 1</i>				
Profile 1	.862	.007	.132	.000
Profile 2	.007	.933	.005	.056
Profile 3	.088	.014	.893	.006
Profile 4	.000	.067	.010	.924
<i>Time 2</i>				
Profile 1	.952	.038	.004	.006
Profile 2	.117	.877	.007	.000
Profile 3	.012	.008	.894	.087
Profile 4	.004	.000	.105	.891

*Note.* Profile 1: *Involved*; Profile 2: *High Presenteeism*; Profile 3: *Low Presenteeism*; and Profile 4: *Problematic*.

**Table S10***Transition Probabilities*

	Profile 1	Profile 2	Profile 3	Profile 4
Profile 1	.786	.214	.000	.000
Profile 2	.106	.851	.043	.000
Profile 3	.000	.023	.818	.160
Profile 4	.000	.000	.219	.781

*Note.* Profile 1: *Involved*; Profile 2: *High Presenteeism*; Profile 3: *Low Presenteeism*; and Profile 4: *Problematic*.

**Table S11***Results from the Predictive Analyses*

Predictors	Profile 1 vs 4		Profile 2 vs 4		Profile 3 vs 4	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Availability expectations	.213 (.199)	1.238	.089 (.195)	1.093	-.364 (.151)*	.695
Challenge demands	1.556 (.370)**	4.738	1.408 (.330)**	4.086	.110 (.270)	1.116
Hindrance demands	-1.893 (.398)**	.151	-1.401 (.367)**	.246	-.115 (.285)	.891
Predictors	Profile 1 vs 3		Profile 2 vs 3		Profile 1 vs 2	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Availability expectations	.577 (.189)**	1.780	.453 (.173)**	1.573	.124 (.172)	1.132
Challenge demands	1.446 (.324)**	4.246	1.298 (.262)**	3.661	.148 (.275)	1.160
Hindrance demands	-1.778 (.337)**	.169	-1.286 (.288)**	.276	-.492 (.303)	.611

*Note.* \*  $p < .05$ ; \*\*  $p < .01$ ; SE: Standard error of the coefficient; OR: Odds ratio; the coefficients and OR reflect the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile; availability expectations through information and communication technology, challenge demands, and hindrance demands are estimated from factor scores with a standard deviation of 1 and a mean of 0; Profile 1: *Involved*; Profile 2: *High Presenteeism*; Profile 3: *Low Presenteeism*; and Profile 4: *Problematic*.