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The dynamics of well-being at work: longitudinal profiles of boredom, burnout, and work engagement

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ABSTRACT
Job boredom, a deactivated and unpleasant affective state experienced at work, can become persistent, leading to negative consequences for individuals and organizations. However, the possible co-existence of job boredom with other workplace well-being indicators, such as burnout and work engagement, is still poorly understood. To address this issue, our research expands upon the predominant variable-centred perspective on boredom and employs a longitudinal person-centred approach to investigate the most salient configurations of job boredom, burnout, and work engagement over time and examine job demands and resources as predictors of profile membership. Across two samples, findings revealed distinct well-being profiles, including high-burnout/low-engagement profiles, alongside bored-and-burned-out and mixed profiles. Role conflict was found to predict unfavourable profiles, while autonomy, learning opportunities, and cognitive demands were linked to more favourable combinations. This study advances understanding of job boredom and its associations with other key aspects of workplace well-being, such as burnout and engagement. The paper offers novel insights into how these aspects can be experienced simultaneously and informs strategies to foster employee well-being by promoting favourable configurations.

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Job boredom; burnout; work engagement; latent profile analyses; latent transition analyses

Job boredom is a widespread but still little-investigated work experience (e.g., Loukidou et al., 2009; Reijseger et al., 2013) and can be defined as a deactivated and unpleasant transient affective state experienced at the workplace (e.g., Schaufeli & Salanova, 2013). Although transient in its nature, research showed that this work-related experience can become persistent and lead to negative consequences at both individual and organizational levels, such as depressive symptoms and turnover intentions (e.g., Loukidou et al., 2009; Reijseger et al., 2013).

Research aimed at understanding psychological well-being at work (see Schaufeli & Salanova, 2013) has often stressed the importance of a holistic lens, considering both positive and negative indicators of well-being. Accordingly, job boredom has been conceptualized and studied alongside well-known psychological states at work, such as burnout and work engagement (e.g., Schaufeli & Salanova, 2013). Burnout refers to a negative state characterized by energy depletion, cynicism, and emotional and cognitive symptoms, while work engagement reflects a positive state of energy and fulfilment at work (Schaufeli & Salanova, 2013).

Different taxonomies of work-related psychological well-being (Harju et al., 2014; Schaufeli & Salanova, 2013; Warr, 1990) state that indicators such as job boredom, burnout, and work engagement can theoretically be conceptualized at different poles and triggered by different working conditions. In fact, these frameworks conceptualized work engagement and burnout as opposite constructs. Job boredom is conceptually related to burnout and also situated as the opposite of work engagement in terms of emotional valence and activation, albeit boredom and burnout still representing different constructs (Reijseger et al., 2013). From a more general perspective, Martela (2025) has conceptualized these constructs in terms of affective well-being (where boredom would be theoretically situated) and conative well-being (burnout and work engagement), while acknowledging overlaps between them (e.g., conative constructs can include affective components). Theories and variable-centred approaches show a consistent pattern of relationships between these variables. Specifically, research showed that boredom correlates negatively with work engagement and positively with burnout (Toscanelli, et al., 2022) and that job boredom

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and burnout are negatively related to work engagement (Schaufeli & Salanova, 2013).

However, in line with Martela's (2025) proposition of possible intersection of affective and conative dimensions of well-being at work, person-centred approaches have shown that these psychological states might co-exist in different combinations. For example, it is possible to be bored and exhausted (Harju et al., 2023), or burned out and engaged (Timms et al., 2012). Still, research on the co-existence of job boredom with other work-related psychological states is scarce. Recent studies emphasize the need to examine whether and how boredom might co-occur with less transient and well-known negative and positive psychological states and in what specific configurations. Moreover, although research has shown that job boredom can combine with exhaustion (Harju et al., 2023), less is known about the co-existence of job boredom with the burnout experience as a whole, including aspects such as cynicism, lack of efficiency, emotional and cognitive impairment (Schaufeli et al., 2020). In addition, although theoretical frameworks conceptualize burnout and engagement as opposites (Harju et al., 2014; Schaufeli & Salanova, 2013; Warr,1990) empirical evidence shows that they can occur simultaneously (Timms et al., 2012). However, even though such models conceptualize job boredom in opposition to work engagement, no research has investigated the possible co-existence of boredom with work engagement. Finally, person-centred longitudinal studies on the associations of job boredom with other well-being indicators are scarce, and the current literature calls for a better understanding of the association of boredom with states of ill-being over time using a longitudinal approach (e.g., Harju et al., 2023). Because job boredom, burnout, and work engagement occupy partially overlapping but non-identical positions in affective-conative space and can co-occur, there is a need for analytical approaches that consider these states jointly rather than in isolation, to distinguish qualitatively different well-being experiences that cannot be inferred from variable-centred approaches.

Addressing these issues is essential for deepening the knowledge of whether boredom might be associated with more persistent detrimental states such as burnout and, consequently, with significant health-related risks. Moreover, a better understanding of how boredom relates to different dimensions of burnout could contribute to clarifying the role of boredom within the broader burnout experience. In fact, given that the burnout experience can be heterogeneous (Leiter, 1993), it is important to understand how it is associated with boredom to achieve a better understanding of how these two experiences are lived by employees. Moreover, because positive and negative states can co-exist (e.g., Timms et al., 2012), in contrast to theoretical implications (e.g., Warr, 1990), it is conceptually important to investigate how negative states such as job boredom are situated in comparison to positive indicators such as work engagement. From this conceptual point of view, examining whether boredom can co-exist with work engagement is especially relevant, because boredom, although generally considered detrimental, may nevertheless overlap with positive psychological experiences. In addition, it is crucial to understand if and how the co-existence of boredom with states of ill-being and well-being persists and evolves over time (Harju et al., 2023) to shed light on the different possible associations of boredom with both detrimental and positive psychological states. Taken together, examining job boredom in relation to both burnout and work engagement allows for a more differentiated conceptual understanding of how boredom is embedded in broader patterns of work-related well-being, encompassing both ill-being and well-being.

In addition to better understanding the emergence and persistence of different well-being profiles, it is essential to consider job characteristics that may foster or hinder them. In well-known frameworks such as the Job Demands-Resources model (Bakker et al., 2022), findings linking job demands and resources to well-being are generally consistent (see Bakker et al., 2022). However, recent research distinguishes between different types of demands that may challenge or disrupt employees' work (i.e., challenging vs. hindering demands) and hence relate differently to well-being (e.g., Bakker et al., 2022). Similarly, job resources may serve different functions – either helping employees cope with demands or promoting growth and fulfilment (e.g., Demerouti & Bakker, 2023). To date, only one study investigated the link between hindering and challenging demands and job boredom (Harju et al., 2023) underscoring the need for further research to gain insight into how distinct types of job demands and resources relate to job boredom, as well as its combination with other well-being states. Deepening our understanding of how contextual characteristics relate to *combinations* of well-being outcomes is important because it could yield important insight from both scientific and practical perspectives. Notably, the consideration of hindering and challenging demands as antecedents of these combinations might help to move from viewing job demands solely as a threat to well-being to a deeper understanding of which demands and resources may be associated with different well-being at work combinations over time.

To address these issues, we will examine three well-being indicators – job boredom, burnout (in its multi-dimensionality), and work engagement – using a longitudinal, person-centred approach. Sample 1 was assessed at two times of measurement while Sample 2 was assessed at three measurement points to assess the stability of the profile combinations over time, as well as transitions between profiles. In both studies, we will examine hindering and challenging demands, as well as two different resources (i.e., learning opportunities and autonomy), as possible predictors of membership in different well-being configurations.

This paper contributes to the literature in several ways. First, it enhances the understanding of job boredom, an area still lacking precise empirical evidence regarding its possible co-occurrence with other work-related states. Notably, it will contribute to increasing the knowledge on the conceptualization of job boredom regarding work engagement and burnout. More broadly, this study advances our understanding of workplace well-being by examining how three key indicators – job boredom, burnout, and work engagement – can co-exist and combine over time. This will provide insights into the possible evolution of these configurations over time, as well as into the possible transitioning of employees across different well-being profiles. Finally, this study will contribute to showing how different job demands and resources might predict the probability of belonging in and transitioning between favourable or unfavourable combinations of well-being states and hence offer a dynamic perspective on work-related well-being.

Profiles of job boredom, burnout, and work engagement

Job boredom, work engagement, and burnout are known indicators of well- and ill-being at work. Two similar theoretical frameworks allow to situate these three indicators within a broader well-being framework: Warr's (1990) model of well-being, adapted by Harju and colleagues (2014) and the taxonomy of well-being by Schaufeli and Salanova (2013). In these frameworks, psychological states are depicted by means of two axes, representing pleasure (vs. displeasure) and activation (vs. deactivation). Within these models, job boredom and burnout are positioned as deactivated and unpleasant states, whereas work engagement is seen as an activated and pleasant one (Harju et al., 2014); however, boredom and burnout represent theoretically distinct psychological states within this space, reflecting qualitatively different states of ill-being (see Schaufeli & Salanova, 2013).

As previously mentioned, person-centred approaches examining job boredom in combination with burnout and work engagement are scarce. To date, only one study exists, and identified the co-existence of job boredom and exhaustion (Harju et al., 2023). In contrast, several studies have explored person-centred approaches to burnout and engagement, typically identifying patterns of high burnout with low engagement, and vice versa (e.g., Timms et al., 2012). These studies have also highlighted less traditional combinations, showing that individuals may simultaneously experience both burnout and engagement (e.g., Mäkikangas et al., 2014; Timms et al., 2012). The paucity of person-centred studies makes it difficult to formulate precise hypotheses about all possible profile combinations. However, drawing on theoretical frameworks that conceptualize well-being along dimensions of activation and valence (Harju et al., 2014; Schaufeli & Salanova, 2013; Warr, 1990), we can expect two theoretically *traditional* profiles to appear: one characterized by low levels of job boredom and burnout with high work engagement, and another characterized by high boredom and burnout with low work engagement.

Hypothesis 1: A profile characterized by low levels of job boredom and burnout (all dimensions), and high levels of work engagement, will be identified.

As noted earlier, burnout is a multidimensional construct. The specific burnout dimensions depend on how burnout is conceptualized. In this study, we consider two conceptualizations: The first includes a lack of efficiency as well as exhaustion and cynicism (see Schaufeli et al., 1996). The second includes emotional and cognitive impairments, and exhaustion and cynicism (see Schaufeli et al., 2020). We draw on two conceptualizations of burnout to capture both classical and contemporary understandings of the construct, which can differ in how burnout-related impairment is theoretically specified. The first model conceptualizes burnout as a syndrome combining exhaustion, cynicism, and reduced professional efficacy (Schaufeli et al., 1996), whereas the more recent model retains exhaustion and mental distance but explicitly operationalizes burnout-related impairment in terms of cognitive and emotional functioning (Schaufeli et al., 2020). Examining both conceptualizations in relation to boredom allows us to examine whether job boredom aligns more strongly with a general loss of efficacy or with specific cognitive and emotional impairments, thereby better clarifying the nature of boredom-burnout co-occurrence at the profile level than would be possible by focusing on only one conceptualization of burnout.

To the best of our knowledge, some evidence has reported the co-occurrence of high levels of exhaustion and job boredom (Harju et al., 2023). Accordingly, we expect to identify a profile characterized by high boredom and high exhaustion. Because boredom and burnout are located in close proximity within dimensional models of work-related well-being – sharing an unpleasant and deactivated quality (Warr, 1990; Schaufeli & Salanova, 2013) – their co-occurrence may extend to other core burnout dimensions, consistent with Martela's (2025) view that affective and conative aspects of well-being are distinct yet partially overlapping. To our knowledge, no study has examined the co-existence of job boredom with the second core burnout dimension, cynicism. Cynicism reflects a perceived loss of meaning in the workplace (Leiter & Schaufeli, 1996) and has also been linked to job boredom in variable-centred studies (e.g., Toscanelli et al., 2024). Variable-centred literature also showed consistent evidence of the associations between job boredom and emotional impairment (e.g., Li et al., 2024), cognitive impairment (e.g., Sousa & Neves, 2021), and lack of efficiency (e.g., Kawada et al., 2024). Hence, it seems reasonable to expect a profile characterized by high levels of job boredom and cynicism as well as high emotional impairment, cognitive impairment, or lack of efficiency.

Hypothesis 2: A profile characterized by high levels of job boredom and burnout (all dimensions), and low levels of work engagement, will be identified.

Following the previously cited literature, it is also plausible to observe a co-existence of work engagement and burnout (e.g., Timms et al., 2012). Because work engagement and exhaustion have been shown to co-exist simultaneously in specific overstimulating conditions (e.g., Innanen et al., 2014) we can expect a profile characterized by high work engagement and high exhaustion. In that configuration, job boredom is expected to be low. This configuration is theoretically coherent because work engagement is characterized by high activation, which can coexist with exhaustion under conditions of sustained effort. In contrast, such a condition should be incompatible with the low-activation state that defines job boredom (Warr, 1990; Schaufeli & Salanova, 2013). Because overstimulation and understimulation represent opposing environmental conditions, boredom is unlikely to co-occur with exhaustion under high engagement, consistent with literature showing that job boredom primarily arises from understimulating situations (e.g., Reijseger et al., 2013).

Hypothesis 3: A profile characterized by high levels of exhaustion and work engagement, and low levels of job boredom will be identified.

Profiles stability and transitions

Longitudinal person-centred approaches allow researchers to investigate two distinct but complementary types of longitudinal stability. The first, within-sample stability, refers to the consistency in the number and shape of profiles across time (Gillet et al., 2024; Morin & Litalien, 2017). The second is within-person stability, and refers to the stability of employees' membership in the profiles (Gillet et al., 2024; Morin & Litalien, 2017). These approaches allow us to distinguish between the stability of the well-being configurations themselves and the stability of individuals' membership in these configurations. Examining both is thus important because they differentiate between the robustness of qualitatively distinct patterns of well-being across time and the degree to which employees' experiences of well-being are persistent or dynamic.

Theories of work-related well-being do not conceptualize well-being states as independent experiences, but as occupying structured and theoretically meaningful positions within broader frameworks of well-being (e.g., Warr, 1990; Schaufeli & Salanova, 2013). Consequently, the combinations of job boredom, burnout and work engagement can be understood as reflecting recurring forms of work-related well-being and ill-being, making it theoretically plausible that similar profile configurations will be observed across measurement occasions. Existing person-centred longitudinal research supports the expectation of within-sample stability in the profiles constituted by our indicators. Prior research has shown that combinations of engagement and burnout consistently retain their shape and number over time (e.g., Gillet et al., 2023; Lehtiniemi et al., 2024; Mäkikangas et al., 2016). Although evidence concerning job boredom is more limited, one study has provided evidence concerning its within-sample stability together with exhaustion (Harju et al., 2023). On the basis of the previously cited literature, we therefore propose that the number and configuration of profiles would remain similar (within-sample stability) over time.

Hypothesis 4: The identified profiles show within-sample stability.

Concerning within-person stability, several factors must be considered. Although the examined states of boredom, burnout, and engagement are typical indicators of well-being at work, it is important to stress that their duration and stability may differ. From a theoretical perspective, burnout and work engagement are conceptualized as persistent work-related psychological states rather than short-lived ones (e.g., Schaufeli & Salanova, 2013). Although job boredom, as a transient state (e.g., Fisher, 1993), can fluctuate, questionnaire-based assessments have shown to capture recurrent experiences of boredom at work rather than momentary episodes (e.g., Game, 2007). In fact, some studies have highlighted a possible bias concerning the measure of job boredom via questionnaires. It has been shown that participants who experience some short moments of boredom tend to forget them and report in questionnaires that they are *never* bored (Game, 2007). This is important because it implies that when measuring boredom with questionnaires, those who show high levels of boredom are probably experiencing it in a rather stable way. Consistently, research showed that it can be experienced, together with exhaustion, in a rather stable way (Harju et al., 2023) because employees tended to remain in this profile rather than transitioning to other profiles.

Concerning burnout and work engagement, scientific evidence is mixed. Studies have shown a prevalence of within-person stability in burnout and engagement profiles in teachers over a year (e.g., Rantanen et al., 2024), while others have detected dynamic changes in well-being (see Mäkikangas et al., 2016). For example, large proportions of transitions have been found in burnout and work engagement profiles over three time points separated by two years (Lehtiniemi et al., 2024), while varied stability across profiles has been highlighted in studies over one year (Gillet et al., 2023). Because our studies are both focused on shorter time lags (three months with two measurement points and six months with three measurement points), we argue that employees' membership in these profiles (within-person stability) would remain mainly stable over time. However, given the previously cited literature, it might be possible to observe transitions between profiles. For this reason, we expect within-person stability to be moderate (50% of the sample stay in the same profile) to high (75% of the sample stay in the same profile) (see Gillet et al., 2023).

Hypothesis 5: Within-person stability of the identified profiles is high to moderate.

Predictors of profiles membership: job demands and resources

According to the Job Demands-Resources model (JD-R, Bakker & Demerouti, 2017; Schaufeli & Bakker, 2004) job demands arise from physical, psychological, social, and organizational loads – also called stressors – that require significant effort on the part of the worker and therefore imply a physiological or psychological cost to the workers (Demerouti et al., 2001). Resources, on the other hand, refer to "those physical, psychological, social or organizational aspects of the job that may (. . .) (1) be functional in achieving work goals; (2) reduce job demands and the associated physiological and psychological costs; (3) stimulate personal growth and development" (Demerouti et al., 2001, p. 501). Literature mainly highlights low demands and low resources as antecedents of job boredom, and low resources and high demands for burnout. In contrast, a functional combination of job demands and resources is typically associated with work engagement (Demerouti et al., 2001; Reijseger et al., 2013).

Even though the division into challenge versus hindrance demands can be ambiguous (see Podsakoff et al., 2023), several studies stress the importance of considering these two types of job demands to fully understand the relationship between stressors and well-being (e.g., Demerouti & Bakker, 2023). Challenging demands present employees with tasks that are stimulating, such as starting a new project (Demerouti & Bakker, 2023). Hindering demands refer to job demands that disrupt employees' work, such as interruptions, excess of bureaucratic tasks, or role conflict (Demerouti & Bakker, 2023).

A similar distinction might be applied to job resources. Some job resources (e.g., job autonomy) might provide employees with the space to be more autonomous or offer them a window of freedom to cope with workday hassles, while other resources, such as task variety or learning opportunities, might contribute to positive stimulation and growth (e.g., Demerouti & Bakker, 2023). These distinctions are particularly relevant for this study because these different types of job demands and resources might relate to well-being outcomes differently.

Because the profiles identified in this study are defined by the joint configuration of job boredom, burnout, and work engagement, job demands and resources that differentially relate to strain, stimulation, control, and opportunities for growth are particularly relevant for understanding why employees are more likely to belong to specific combinations of our well-being indicators. Challenging job demands relate both to exhaustion and engagement (Demerouti & Bakker, 2023; Rošková & Faragová, 2020) and, given their stimulating nature, might be negatively associated with job boredom (Harju et al., 2023). In turn, hindering job demands, given their strain-inducing and work-disrupting nature, relate to increased exhaustion and boredom (Harju et al., 2023). Concerning job resources, resources such as job autonomy, given their control-enhancing nature, are associated with positive outcomes such as work engagement (see Demerouti & Bakker, 2023) and might be useful to buffer the effects of job demands. Other types of resources might be functional for personal development and growth, such as skill discretion and learning opportunities, and have shown strong positive associations with positive outcomes such as work engagement (see Demerouti & Bakker, 2023) and negative associations with negative outcomes such as burnout and boredom (see Demerouti & Bakker, 2023). The distinction between these types of job resources is relevant concerning job boredom, because the first type has been shown to be less effective than the second type in counteracting it (Toscanelli et al., 2021).

Accordingly, we selected specific indicators of job demands and resources that have been linked to boredom, burnout, and work engagement in prior research, that can capture elements of stimulation, hindrance, control, and growth, and are in line with key motivational and strain JD-R processes (see Demerouti & Bakker, 2023). On this basis, we consider cognitive demands as a challenging demand, and role conflict as a hindering job demand. To reflect different types of job resources, we include job autonomy, which refers to the degree of control employees have over their tasks, and learning opportunities, which involve access to activities that foster personal and professional growth.

Hypothesis 6a: Cognitive demands will positively predict membership in profiles characterized by high burnout and work engagement and negatively predict membership in profiles with high boredom.

Hypothesis 6b: Role conflict will positively predict membership in less favourable profiles (i.e., high burnout, high boredom, low work engagement profiles).

Hypothesis 7a: Autonomy will predict membership in profiles characterized by low burnout and boredom, and high work engagement.

Hypothesis 7b: Learning opportunities will predict membership in profiles characterized by low boredom and burnout, and high work engagement

Method

Participants and procedure

Sample 1 and Sample 2 were composed of workers from the French-speaking part of Belgium. Participants were recruited via a convenience-snowball approach: undergraduate students distributed an online survey link to adults who were employed (full- or part-time) within their personal networks (e.g., friends, family, co-workers) and fluent in the survey language. Upon clicking the link, respondents reviewed an informed-consent statement outlining study purpose, confidentiality, voluntary participation, and withdrawal rights; those who consented completed the first-wave questionnaire online. At the end of the survey, participants were asked to provide a valid e-mail address if they wished to be recontacted for subsequent waves. E-mail addresses were stored separately from survey data and used solely for follow-up invitations. No incentives were offered, and participation was entirely voluntary.

Concerning Sample 1, Wave 1 took place from mid-October to mid-December 2023 ($N = 743$) while Wave 2 took place 4 months later, from mid-February to mid-March 2024 ($N = 282$). In this sample, all the participants who answered to at least one measurement wave were retained, resulting in a final sample of $N = 743$ participants working in various occupational sectors ($N = 743$, $M_{age} = 40.86$, 70.8% women; 76.5% held a university degree, 79.2% working full-time).

Sample 2 included three waves of measurement separated by three months. Wave 1 took place at the end of October 2022 ($N = 2208$). A total of 1028 Participants shared their email address to be recontacted for future waves. Of those, 318 participants completed Wave 2, which took place at the end of January 2023 ($N = 318$) and Wave 3, which took place at the end of April 2023 ($N = 252$). Given that the present study focuses on the stability of well-being profiles and transitions between profiles over time, only participants who answered on at least two measurement times were retained for the analyses. This decision was made to minimize reliance on inferred longitudinal information (Collins & Lanza, 2010; Nylund-Gibson & Choi, 2018), thereby ensuring that the sample provided sufficient repeated observations to estimate within-person transitions across the three time points. The final sample was composed of $N = 374$ participants working in various professional sectors ($M_{age} = 41.65$, 75.4% women, 60.6% held a university degree, 73% working full-time).

Time-lags between the measurements in both samples were made to reflect common time-lags used in research examining the same indicators (see Mäkikangas et al., 2016). These constructs are conceptualized as work-related psychological states that may change over time, yet typically do so gradually rather than abruptly (Schaufeli & Salanova, 2013). In contrast to other studies on job boredom that employed longer time-lags (6 to 18 months, see Harju et al., 2023), we intentionally chose somewhat shorter lags to better capture possible dynamics in profiles, while still allowing to show potential stability of profiles over several months. The chosen time-lags should thus be long enough to assess meaningful change over time but also short enough to capture fluctuations on the assessed well-being states.

Given the person-centred focus of the present study, careful consideration was given to how work-related well-being indicators were represented in the analyses. Job boredom was modelled as a unidimensional construct, reflecting its common conceptualization and measurement in the literature (Schaufeli & Salanova, 2013). Burnout was represented through theoretically distinct dimensions, in line with the conceptual arguments outlined in the Introduction and with measurement recommendations cautioning against the use of an overall burnout score when distinct components capture qualitatively different aspects of the syndrome (Maslach, 1993; Maslach & Jackson, 1986). Work engagement was modelled as a unidimensional construct capturing overall engagement. This choice was guided by evidence showing that global engagement scores provide a reliable representation of overall engaged state (Schaufeli et al., 2006). Modelling engagement at a global level allowed for a parsimonious and balanced representation of well-being indicators in the identification of profiles, without disproportionately weighting constructs assessed using a larger number of dimensions.

Measures

Sociodemographic controls were assessed in both studies and included age, gender and job tenure because prior research shows that these background factors are related to levels of burnout, job boredom, and work engagement. For example, older workers often report lower burnout and higher engagement than younger employees (Maslach et al., 2001), women and men can experience different patterns of exhaustion and vigour (Schaufeli & Bakker, 2004), and longer job tenure tends to buffer against boredom but can also be associated with plateau effects that influence engagement (Demerouti et al., 2001). Controlling for these demographics ensures that observed effects on burnout, boredom, and engagement are not confounded by age, gender, or tenure.

Job boredom

Job boredom was assessed using two established self-report instruments to ensure that the results are robust across commonly adopted operationalizations of job boredom and to reduce the likelihood that the findings reflect scale-specific measurement characteristics. In *Sample 1*, job boredom was assessed with the *Job Boredom Scale* (Van Hooff & van Hooft, 2014) composed of 5 items rated on a 5-point Likert scale ranging from 1 (never) to 5 (always) (e.g., "I think my work is boring"). This scale showed good reliability at the two measurement times ($\alpha_{wave1} = .93$; $\alpha_{wave2} = .94$). In *Sample 2*, job boredom was measured with the *Dutch Boredom Scale* (DUBS, Reijseger et al., 2013) composed of 6 items rated on a 7-point Likert scale ranging from 1 (never) to 7 (always) in its French version (Toscanelli et al., 2021). We removed three items from the original scale since they referred to coping strategies and antecedents of job boredom and were deemed inappropriate to represent the core construct of job boredom, in line with recent research (Van Hooff & van Hooft, 2014). This scale showed good reliability at the three measurement times ($\alpha_{wave1} = .80$; $\alpha_{wave2} = .86$; $\alpha_{wave3} = .88$).

Burnout

Burnout was assessed using two established self-report instruments corresponding to two complementary conceptualizations of the construct. In *Sample 1*, burnout and its three subdimensions were measured with the *General version of the Maslach Burnout Inventory* (MBI-GS; Schaufeli et al., 1996) in its French version (Bocéréan et al., 2019). *Exhaustion* was measured with 5 items (e.g., "I feel emotionally drained from my work"), *cynicism* with 5 items (e.g., "I have become more cynical about whether my work contributes anything") and *lack of efficiency* with 6 items (e.g., I think I'm pretty efficient in my work"; reversed) rated on a 7-point Likert scale ranging from 1 (never) to 7 (always). All the scales and subscales showed acceptable to good reliability at both times of measure, respectively exhaustion ($\alpha_{wave1} = .88$; $\alpha_{wave2} = .90$), cynicism ($\alpha_{wave1} = .83$; $\alpha_{wave2} = .85$), and lack of efficiency ($\alpha_{wave1} = .80$; $\alpha_{wave2} = .81$). In *Sample 2*, burnout and its four subdimensions were measured with the *Burnout Assessment Tool* (BAT, Schaufeli et al., 2020) in its French version (Schaufeli et al., 2019). This measure of burnout includes four subdimensions. The first is *exhaustion* and is measured by 3 items (e.g., "At work, I feel mentally exhausted"). The second is *mental distance* and it is measured by 3 items (e.g., "I'm cynical about what my work means to others"), the two others refer to *cognitive* (e.g., "At work, I have trouble staying focused") and *emotional* (e.g., "At work I may overreact unintentionally") *impairment* and were measured with three items each. All the subscales showed acceptable to good reliability at both times of measure, respectively exhaustion ($\alpha_{wave1} = .80$; $\alpha_{wave2} = .80$; $\alpha_{wave3} = .85$), distance ($\alpha_{wave1} = .84$; $\alpha_{wave2} = .79$;

α_{wave3} = .85), cognitive impairment (α_{wave1} = .76; α_{wave2} = .80; α_{wave3} = .83), and emotional impairment (α_{wave1} = .87; α_{wave2} = .84; α_{wave3} = .88).

Work engagement

In *both samples*, work engagement was measured with the *Utrecht Work Engagement Scale* (UWES, Schaufeli et al., 2006) in its French validation (Zecca et al., 2015) in its short version, hence in its unidimensional form (e.g., "At my work, I feel bursting with energy"). The scale showed good reliability at the two measurement times (α_{wave1} = .86; α_{wave2} = .86), in Sample 1, and at the three measurement times in Sample 2 (α_{wave1} = .84; α_{wave2} = .85; α_{wave3} = .86).

Job demands and resources

In *both samples*, working conditions were measured with the *JD-R questionnaire* (Bakker, 2014) and the *Short Inventory to Monitor Psychosocial Hazards* (SIMPH, Notelaers et al., 2007). *Cognitive demands* (e.g., "Does your work require sustained attention or precision?") were assessed with the JD-R questionnaire and were composed of 3 items. *Role conflict* (hindering demands, e.g., "Do you receive contradictory instructions?") was assessed with the SIMPH and was composed of 3 items. Job resources included *opportunities to learn* (e.g., "Do you learn new things in your job?") and *autonomy* (e.g., "Can you determine the order of your tasks by yourself?") and were assessed with the respective 3-item subdimensions of the SIMPH. To facilitate completion, the response scale has been adapted following the SIMPH rating format. Hence, each item was rated on a 4-point Likert scale ranging from 1 (always) to 4 (never), with scores being subsequently reversed. All the scales showed acceptable to good reliability at both measurement times in Sample 1, respectively role conflict (α_{wave1} = .71; α_{wave2} = .70), cognitive demands (α_{wave1} = .79; α_{wave2} = .82), learning opportunities (α_{wave1} = .79; α_{wave2} = .79), and autonomy (α_{wave1} = .70; α_{wave2} = .73), and at the three measurement times in Sample 2, respectively role conflict (α_{wave1} = .72; α_{wave2} = .70; α_{wave3} = .70), cognitive demands (α_{wave1} = .81; α_{wave2} = .82; α_{wave3} = .82), learning opportunities (α_{wave1} = .80; α_{wave2} = .80; α_{wave3} = .83) and autonomy (α_{wave1} = .73; α_{wave2} = .74; α_{wave3} = .74)

Data analytical approach

All analyses of the two studies were conducted using the robust maximum likelihood estimator (MLR) in M*Plus* 8.6 (Muthén & Muthén, 2021). Preliminary analyses involved attrition analyses, factor analyses, and longitudinal measurement invariances analyses to establish the equivalence of measures across time points. Specifically, configural, metric, scalar, and strict invariance were sequentially tested for all profile indicators and predictors in both samples (see Tables S1 and S2 in the Supplementary Materials). Following guidelines for conducting latent profile and transition analyses, factor scores from the most invariant longitudinal models were retained to ensure comparability between profiles and studies (e.g., Huyghebaert-Zouaghi et al., 2022). All factor scores were estimated in standardized units (*SD* = 1; *M* = 0). Consistent with established guidelines, we used Full Information Maximum Likelihood (FIML) procedures to handle missing data in both studies (Newman, 2014). Attrition was evaluated in each sample following recommended practice (Enders, 2022). We regressed dropout status (0 = complete, 1 = partial) on gender, age, and tenure using logistic regression, and compared baseline means of profile indicators (i.e., boredom, burnout dimensions, and engagement) between complete and partial respondents with independent-samples t-tests. None of the demographic variables predicted attrition (*ps* > .05) and profile indicators did not differ between complete and partial respondents (*ps* > .05). These findings suggest that missingness can be treated as missing at random and support the use of FIML in subsequent models.

Latent profile analyses (LPA)

We used LPA to identify latent subpopulations, called profiles, of participants which are characterized by distinct configurations on a specific set of indicators (Spurk et al., 2020). Compared to classical clustering techniques, LPA and mixture models are probabilistic in nature as each participant is assigned a probability of membership. This specificity accounts for classification errors of participants into profiles and allows to incorporate antecedents and consequences in a flexible and longitudinal framework.

Time-specific LPA models were estimated using the well-being factors as indicators, that is, job boredom, exhaustion, cynicism, lack of efficiency, and work engagement in Sample 1, and job boredom, exhaustion, mental distance, cognitive impairment, emotional impairment, and work engagement in Sample 2. LPA models including 1 to 8 profiles were estimated with the means and variances allowed to be freely estimated, using 5000 sets of random start values with final stage optimization being conducted on the 200 best solutions. These parameters were adapted to 10,000 and 500 for longitudinal and latent transition analyses.

Model comparison and selection

The comparison and selection of LPA models rely on statistical and theoretical grounds, ensuring that the profiles are parsimonious, statistically proper, make sense theoretically, carry substantive meaning, and are not redundant (Spurk et al., 2020). The best profile solutions should display lower values on several fit statistics: the Akaike Information Criterion (AIC), the Consistent AIC (CAIC), the Bayesian Information Criterion (BIC), and the sample-size adjusted BIC (SABIC). Profile solutions should also display entropy values greater than .70. Given the dependency of LPA to sample size, it is recommended to carefully analyse these fit statistics individually but also to look at their overall graphical pattern and the possible identification of a plateau in the decrease of these indicators, suggesting that adding profiles does not yield additional information and helping to identify the optimal solution.

Longitudinal test of profile similarity

Following time-specific LPA models, longitudinal LPA models were then estimated, and longitudinal tests of profile similarity were carried out (Morin & Litalien, 2017; Morin et al., 2016). Longitudinal tests of profile similarity follow a sequential approach by increasingly placing equality constraints and test (a) whether the same profiles emerge across measurement points (configural similarity), (b) the equivalence of within-profile means (structural similarity), (c) the equivalence of within-profile variances (dispersion similarity), (d) and the equivalence of within-profile sizes (distributional similarity). Similarity models were retained when at least two of the *Consistent Akaike Information Criterion* (CAIC), *Bayesian Information Criterion* (BIC), and *Sample-size Adjusted Bayesian Information Criterion* (SABIC) indices decreased compared to the previous models (Morin et al., 2016).

Latent transition analyses (LTA)

Following the identification of the best profile similarity model, we investigated the within-person stability in, and transitions across, profiles by conducting LTA models. These models were specified using the manual three-step approach (Asparouhov & Muthén, 2014; see; Morin & Litalien, 2019 for a technical description). Next, we tested the relations between predictors and profile stability and transitions, and whether these relations remained stable over time (i.e., predictive similarity). First, we estimated a model in which predictors were freely estimated and allowed to predict both time-specific profile membership and profile transitions over time. Second, we estimated a model in which predictors were allowed to predict time-specific profile membership only. Finally, a model of predictive similarity was estimated and constrained the influence of predictors to be the same across measurement points.

Results

Descriptives

The descriptive statistics, reliability coefficients, and bivariate correlations for Sample 1 and Sample 2 are reported in the supplementary material in Tables S1 and S2, respectively, and show meaningful and theoretically consistent relationships across constructs in both samples.

Identifying boredom-engagement-burnout profiles

Concerning Sample 1, the statistical indices associated with each of the time-specific LPA solutions are reported in Table S5 and are graphically illustrated in Figures S1 and S2. Fit indices continuously decreased up to the eighth solution but, at both measurement points, there seemed to be a plateau around the fifth profile. Solutions including four to five profiles were thus examined in detail. This examination revealed that adding profiles resulted in a meaningful contribution to the solution up to five profiles (i.e., each additional profile presented a well-differentiated and meaningful shape) but adding a profile from 5 to 6 profiles added no additional information, whether from a qualitative (e.g., shape) or quantitative (e.g., mean levels) point of view. Hence, the five-profiles solution was retained based on fit criteria and interpretability at both measurement points.

Concerning the longitudinal test of profiles similarity in Sample 1, the fit indices from all longitudinal models are reported in Table 1.

Starting with a model of *configural* similarity including five profiles at each time point, equality constraints were progressively integrated. The second model of *structural* similarity, constraining the mean levels of profile indicators to be the same across time, and the third model of *dispersion* similarity, constraining the within-profile variances to be equal over time, resulted in lower BIC and CAIC values, and was thus supported by the data. However, the model of *distributional* similarity yielded in higher fit indices values and the *dispersion* similarity model was retained as the best description of the data. This model is graphically represented in Figure 1, and detailed parameter estimates from this

Table 1. Sample 1 longitudinal test of profile similarity: 5 profiles.

Model	LL	#fp	Scaling	AIC	CAIC	BIC	SABIC	Entropy
Latent Profile analysis: 5 Profiles								
Configural Similarity	−6120.273	108	1.036	12456.546	13057.747	12949.747	12606.821	0.877
Structural Similarity	−6188.770	83	1.121	12543.540	13005.574	12922.574	12659.028	0.879
Dispersion Similarity	**−6249.370**	**58**	1.116	**12614.741**	**12937.608**	**12879.608**	**12695.443**	**0.876**
Distributional Similarity	−6265.970	54	1.181	12639.939	12940.540	12886.540	12715.076	0.886
Latent transition analysis with predictors								
Null Effects Model	−5356.521	186	1.6736	11085.042	12120.443	11934.443	11343.847	0.935
Free Relations with Predictors	−5401.184	106	1.5287	11014.368	11604.435	11498.435	11161.859	0.930
Equal Relations with Predictors	−5408.572	90	1.5154	10997.144	11498.144	11408.144	11122.372	0.928

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

model are reported in Tables S6. In Sample 1, the five-profile solution is depicted in Figure 1 and is composed as follows.

Profile 1 (30.98%$_{\text{Time1}}$, 34.00%$_{\text{Time2}}$) represents average levels on all the indicators and is labelled *average profile*. Profile 2 (12.34%$_{\text{Time1}}$, 12.52%$_{\text{Time2}}$) represents strongly low levels of work engagement, strongly high levels of cynicism and boredom, high levels of exhaustion and lack of efficiency. This profile is labelled *burned out, cynical and bored profile*. Profile 3 (11.84%$_{\text{Time1}}$, 2.88%$_{\text{Time2}}$) represents high levels of work engagement, low cynicism and boredom, relatively low exhaustion and lack of efficiency. This profile is labelled *engaged profile*. Profile 4 (18.34%$_{\text{Time1}}$, 22.28%$_{\text{Time2}}$) is similar to profile 3, but differs in terms of the intensity on the indicators. It is labelled *relatively engaged profile*. Finally, profile 5 (26.51%$_{\text{Time1}}$, 28.32%$_{\text{Time2}}$) represents especially relatively high cynicism, with average-high exhaustion, lack of efficiency and boredom, average-low engagement. This profile is labelled *relatively burned out, cynical and bored*.

Concerning Sample 2, the statistical indicators associated with each of the time-specific LPA solutions are reported in Table S7 of the supplementary material and are graphically illustrated in Figures S3 to S5 in the supplementary material. Following these results, solutions including four to five profiles were thus examined. This examination revealed that adding profiles resulted in a meaningful contribution to the solution up to five profiles (i.e., each additional profile presented a well-

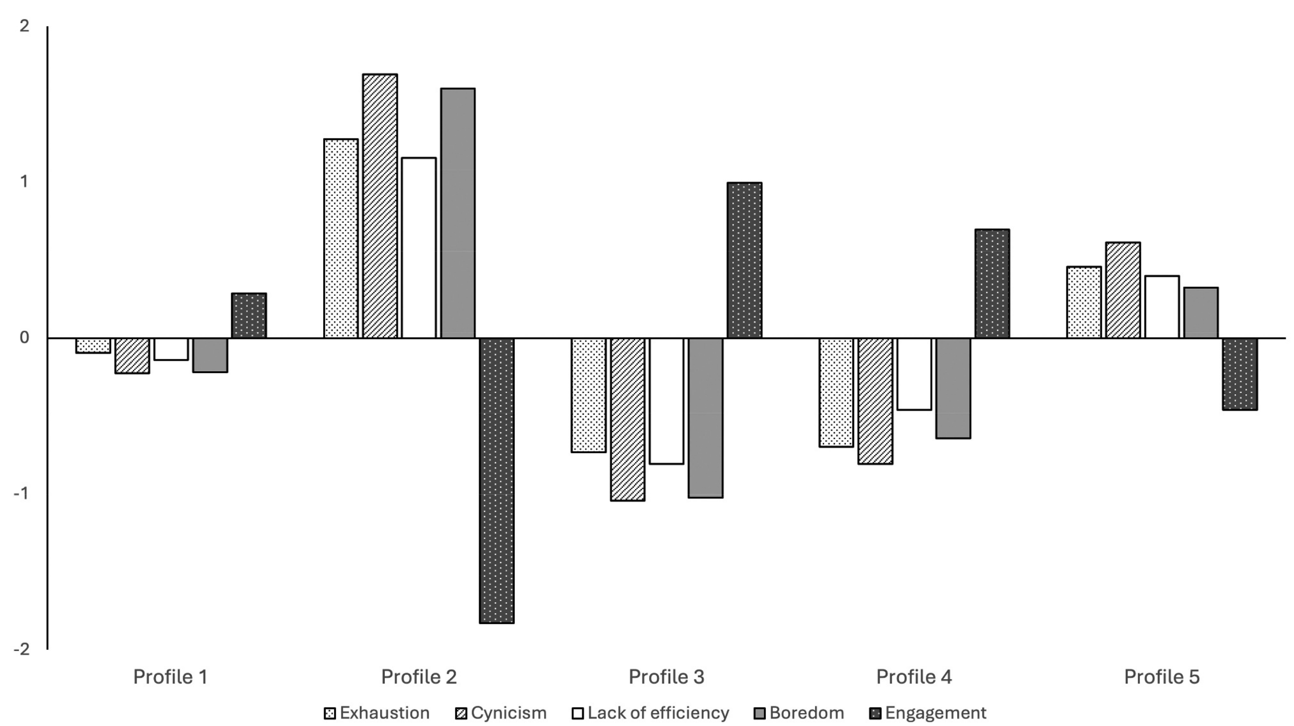

Figure 1. Result of the LTA without starts in Sample 1. For easier interpretation, the graph is based on z scores. Profile 1 = average profile; Profile 2 = burned out, cynical and bored profile; Profile 3 = engaged profile; Profile 4 = relatively engaged profile; Profile 5 = relatively burned out, cynical and bored profile.

differentiated and meaningful shape). Hence, the five profiles was retained based on fit criteria and interpretability and could be replicated in the three measurement points. Concerning the longitudinal test of profiles similarity in Sample 2, the fit indices from all longitudinal models are reported in Table 2.

Starting with a model of *configural* similarity including five profiles per time point, equality constraints were progressively integrated. The second model of *structural* similarity resulted in lower BIC and CAIC values and was thus supported by the data. Likewise, the *dispersion* and *distributional* similarity of the solution was also supported by the data, resulting in lower BIC, SABIC, and CAIC values. The model of *distributional* similarity was thus retained for interpretation and further analyses. This model is graphically represented in Figure 2, and detailed parameter estimates from this model are reported in Tables S8 in the supplementary material. Although profile proportions were constrained to be equal across time in the retained distributional similarity model, small variations in the time-specific percentages reflect posterior classification summaries rather than model-implied class proportions. In Sample 2, the retained five-profile solution is depicted in Figure 2 and was composed as follows.

Profile 1 shows very high mental distance and job boredom, very low engagement, relatively high exhaustion, and cognitive and emotional impairment. This profile is labelled *burned out, cynical and bored profile* (16.76%$_{\text{Time1}}$, 18.32%$_{\text{Time2}}$, 18.61%$_{\text{Time3}}$). Profile 2

Table 2. Sample 2 longitudinal test of profile similarity: 5 profiles.

Model	LL	#fp	Scaling	AIC	CAIC	BIC	SABIC	Entropy
Latent Profile analysis: 5 Profiles								
Configural Similarity	−6699.170	192	1.1582	13782.033	14727.490	14535.490	13926.328	0.881
Structural Similarity	−6768.694	132	1.3321	13801.387	14451.390	14319.389	13900.590	0.860
Dispersion Similarity	−6813.900	72	2.2043	13771.800	14126.350	14054.346	13825.911	0.852
Distributional Similarity	**−6816.654**	**64**	**2.4888**	**13761.309**	**14076.460**	**14012.461**	**13809.407**	**0.851**
Latent transition analysis with predictors								
Null Effects Model	−5841.895	312	0.7157	12307.790	13844.158	13532.158	12542.269	0.966
Free Relations with Predictors	Non-convergence							
Equal Relations with Predictors	**−5909.538**	**120**	**1.5524**	**12059.075**	**12649.986**	**12529.986**	**12149.259**	**0.963**

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

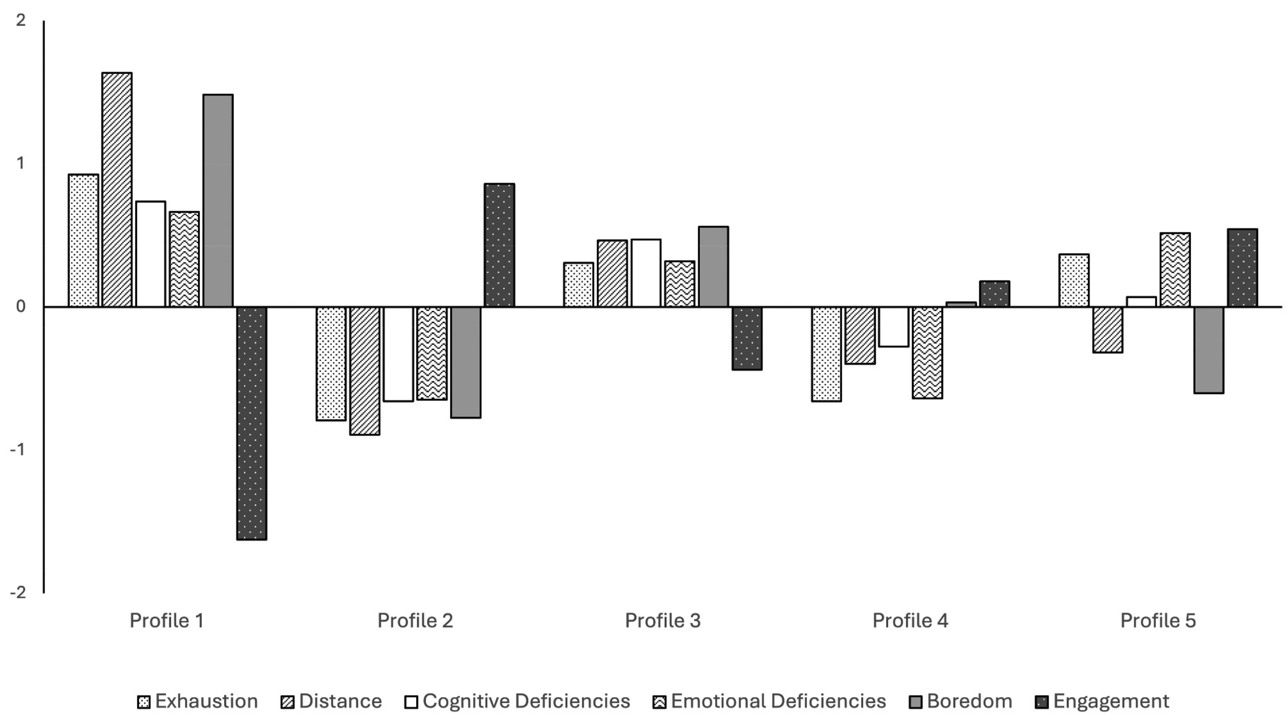

Figure 2. Result of the LTA with starts in Sample 2. For easier interpretation, the graph is based on z scores. Cog. Def. = cognitive impairment; Em. Def. = emotional impairment. Profile 1 = burned out, cynical and bored profile; Profile 2 = engaged profile; Profile 3 = relatively burned out, cynical and bored profile; Profile 4 = averagely bored and engaged profile; Profile 5 = engaged, exhausted and emotionally impaired profile.

Table 3. Transition probabilities/odds and 95% CI for the odds (in parentheses) across profiles in Sample 1.

	Profile 1 T2	Profile 2 T2	Profile 3 T2	Profile 4 T2	Profile 5 T2
Profile 1 T1	0.938/ 1.00 (1.00, 1.00)	0.000/0.00 (0.00, 0.00)	**0.006/0.01 (0.00, 0.13)**	0.004/0.00 (0.00, 3.43)	**0.053/0.06 (0.02, 0.16)**
Profile 2 T1	0.004/ 0.00 (0.00,108.57)	0.959/1.00 (1.00, 1.00)	0.000/0.00 (0.00, 0.00)	**0.019/0.02 (0.00, 0.25)**	**0.018/0.02 (0.00, 0.16)**
Profile 3 T1	0.133/ 0.99 (0.16, 6.10)	0.000/0.00 (0.00, 0.00)	**0.135/1.00 (1.00, 1.00)**	**0.732/5.44 (2.12, 13.94)**	0.000/0.00 (0.00, 0.00)
Profile 4 T1	**0.182/ 0.25 (0.08, 0.81)**	0.000/0.00 (0.00, 0.00)	**0.054/0.07 (0.02, 0.23)**	**0.723/1.00 (1.00, 1.00)**	**0.041/0.06 (0.02, 0.17)**
Profile 5 T1	0.000/ 0.00 (0.00, 0.00)	**0.026/0.03 (0.01, 0.09)**	**0.004/0.00 (0.00, 0.08)**	0.000/0.00 (0.00, 0.00)	0.970/1.00 (1.00, 1.00)

Note. Significant results are depicted in bold. Profile 1 = average profile; Profile 2 = burned out, cynical and bored profile; Profile 3 = engaged profile; Profile 4 = relatively engaged profile; Profile 5 = relatively burned out, cynical and bored profile.

represents high levels of work engagement, low levels of boredom and burnout ($21.54\%_{\text{Time1}}$, $21.13\%_{\text{Time2}}$, $21.13\%_{\text{Time3}}$). This profile is labelled *engaged profile*. Profile 3 shows relatively high levels of boredom, average high burnout, average low engagement. This profile is labelled *relatively burned out, cynical and bored* ($18.67\%_{\text{Time1}}$, $20.19\%_{\text{Time2}}$, $20.22\%_{\text{Time3}}$). Profile 4 shows relatively low exhaustion and emotional impairment, average-low distance and cognitive impairment, average boredom and engagement. This profile is labelled *averagely bored and engaged* ($20.94\%_{\text{Time1}}$, $21.10\%_{\text{Time2}}$, $20.77\%_{\text{Time3}}$). Profile 5 shows relatively high emotional impairment and engagement, relatively low boredom, average-low distance, average-high exhaustion. This profile is labelled *engaged, exhausted and emotionally impaired* ($22.08\%_{\text{Time1}}$, $19.27\%_{\text{Time2}}$, $19.27\%_{\text{Time3}}$).

These results are in line with Hypotheses 1 and 2. However, Hypothesis 3 was partially confirmed. In fact, a profile characterized by high levels of engagement and exhaustion emerged only in Sample 2 (Profile 5).

Transitions

Concerning Sample 1, Table 3 shows the results of the latent transition analysis. Results show that, except for Profiles 3 and 4, employees have higher probability to stay in the same profile over time than to transition to other profiles. However, results showed significant probabilities of transition for different profiles over time. Participants in the *average profile* had 1% and 5% of probability to transition to Profile 3 (*engaged profile)* and Profile 5 (*relatively burned out, cynical and bored)* respectively. Participants in Profile 2 (*burned out, cynical and bored profile)* had 2% of probability to transition to Profile 4 (*relatively engaged profile)* and Profile 5 (*relatively burned out, cynical and bored)* respectively. Participants in Profile 3 (engaged profile) were more likely to transition to Profile 4 *relatively engaged profile* (73% of probability). However, participants in Profile 4 (*relatively engaged profile)* had 18% of probability to transition to Profile 1 (average profile), 5% to Profile 3 (*engaged profile)* and 4% Profile 5 (*relatively burned out, cynical and bored)*. Finally, participant in Profile 5 (*relatively burned out, cynical and bored*) had 3% of probability to transition to Profile 2 (*burned out, cynical and bored profile)*.

Latent transition analyses in Sample 2, results are depicted in Tables 4 and 5. In contrast to the results of Sample 1, the results of Sample 2 show that except for minor changes, employees have a higher probability to stay in the same profile over time than to transition to other groups.

These results confirm Hypotheses 4 and 5 in both samples. In fact, within-sample stability has been confirmed in both samples, while within-person stability has been shown to be high in Sample 2, and moderate in Sample 1.

Examining the associations between profile membership and work characteristics

Table 6 shows the odds ratio of probabilities for different profiles under the effect of covariates in Sample 1, while Table 7 shows the odds ratio of probabilities for different profiles under the effect of covariates in Sample 2.

Hypothesis 6a was only partially supported. In both samples, cognitive demands positively predicted membership in profiles characterized by high burnout but also by high boredom and low work engagement. In fact, cognitive demands positively predicted

Table 4. Time 1 to time 2 transition probabilities/odds and 95% CI for the odds (in parentheses) across profiles in Sample 2.

	Profile 1 T2	Profile 2 T2	Profile 3 T2	Profile 4 T2	Profile 5 T2
Profile 1 T1	0.894/ 1.00 (1.00, 1.00)	0.000/ 0.00 (0.00, 0.00)	0.058/ 0.10 (0.00, 0.20)	0.048/ 0.10 (0.00, 0.20)	0.000/ 0.00 (0.00, 0.00)
Profile 2 T1	0.000/ 0.00 (0.00, 0.00)	0.931/ 1.00 (1.00, 1.00)	0.023/ 0.00 (0.00, 0.10)	0.045/ 0.00 (0.00, 0.20)	0.000/ 0.00 (0.00, 0.00)
Profile 3 T1	**0.136/ 0.20 (0.10, 0.40)**	0.000/ 0.00 (0.00, 0.00)	0.802/ 1.00 (1.00, 1.00)	0.033/ 0.00 (0.00, 0.40)	0.029/ 0.00 (0.00, 0.20)
Profile 4 T1	0.000/ 0.00 (0.00, 0.00)	0.000/ 0.00 (0.00, 0.00)	0.107/ 0.10 (0.00, 0.30)	0.893/ 1.00 (1.00, 1.00)	0.000/ 0.00 (0.00, 0.00)
Profile 5 T1	0.036/ 0.00 (0.00, 0.10)	0.049/ 0.01 (0.00, 0.20)	0.068/ 0.10 (0.00, 0.20)	0.000/ 0.00 (0.00,0.00)	0.848/ 1.00 (1.00, 1.00)

Note. Significant results are depicted in bold. Profile 1 = burned out, cynical and bored profile; Profile 2 = engaged profile; Profile 3 = relatively burned out, cynical and bored profile; Profile 4 = averagely bored and engaged profile; Profile 5 = engaged, exhausted and emotionally impaired profile.

Table 5. Time 2 to time 3 transition probabilities/odds and 95% CI for the odds (in parentheses) across profiles in Sample 2.

	Profile 1 T3	Profile 2 T3	Profile 3 T3	Profile 4 T3	Profile 5 T3
Profile 1 T2	1.000/ 1.00 (1.00, 1.00)	0.000/ 0.00 (0.00, 0.00)	0.000/ 0.00 (0.00, 0.00)	0.000/ 0.00 (0.00, 0.00)	0.000/ 0.00 (0.00, 0.00)
Profile 2 T2	0.000/ 0.00 (0.00, 0.00)	1.000/ 1.00 (1.00, 1.00)	0.000/ 0.00 (0.00, 0.00)	0.000/ 0.00 (0.00, 0.00)	0.000/ 0.00 (0.00, 0.00)
Profile 3 T2	0.015/ 0.02 (0.00,1.12)	0.000/ 0.00 (0.00, 0.00)	0.985/ 1.00 (1.00, 1.00)	0.000/ 0.00 (0.00, 0.00)	0.000/ / 0.00 (0.00, 0.00)
Profile 4 T2	0.000/ 0.00 (0.00, 0.00)	0.000/ 0.00 (0.00, 0.00)	**0.016/ 0.02 (0.002,0.130)**	0.984/ 1.00 (1.00, 1.00)	0.000/ / 0.00 (0.00, 0.00)
Profile 5 T2	0.000/ 0.00 (0.00, 0.00)	0.000/ 0.00 (0.00, 0.00)	0.000/ 0.00 (0.00, 0.00)	0.000/ 0.00 (0.00, 0.00)	1.000/ 1.00 (1.00, 1.00)

Significant results are depicted in bold. Profile 1 = burned out, cynical and bored profile; Profile 2 = engaged profile; Profile 3 = relatively burned out, cynical and bored profile; Profile 4 = averagely bored and engaged profile; Profile 5 = engaged, exhausted and emotionally impaired profile.

membership in high boredom profiles in Sample 1 and increased the probability of belonging to Profile 2 (*burned out, cynical and bored profile)* compared to Profile 1 (*average profile)*. In Sample 2, results indicated that higher cognitive demands increased the probability of belonging to Profile 1 *(burned out, cynical, and bored)* compared to other profiles.

Consistently with Hypothesis 6b, in both samples, role conflict positively predicted membership in less favourable profiles (i.e., high burnout, high boredom and low work engagement profiles). In Sample 1, higher levels of role conflict increased the probability of belonging to Profile 5 (*relatively burned out, cynical and bored)* compared to Profile 1 (*average profile)*, 3 (*engaged profile)*, and 4 (*relatively engaged profile)*. Moreover, higher levels of role conflict increased the probability of belonging to Profile 4 (*relatively engaged profile)* compared to Profile 3 (*engaged profile)*. Then, higher levels of role conflict increased the probability of belonging to Profile 2 (*burned out, cynical and bored profile)* compared to Profile 1 (*average profile)*, 3 (*engaged profile*) and 4 (*relatively engaged profile)*. Finally, higher levels of role

Table 6. Results from predictive analysis in Sample 1 - predictors of the profiles.

Predictor variable	Compared profile	Coeff (SE)	Odds ratio	95% CI
Cognitive demands	2 vs **1**	0.468* (.24)	1.596	[1.006, 2.534]
	3 vs **1**	0.294 (.21)	1.342	[0.885, 2.035]
	4 vs **1**	0.119 (.15)	1.126	[0.842, 1.506]
	5 vs **1**	0.207 (.14)	1.230	[0.932, 1.622]
	3 vs **2**	−0.174 (.31)	0.841	[0.455, 1.552]
	4 vs **2**	−0.349 (.27)	0.705	[0.418, 1.190]
	5 vs **2**	−0.261 (.23)	0.770	[0.489, 1.215]
	4 vs **3**	−0.175 (.23)	0.839	[0.537, 1.310]
	5 vs **3**	−0.087 (.24)	0.916	[0.568, 1.477]
	5 vs **4**	0.088 (.18)	1.092	[0.774, 1.541]
Role conflict	2 vs **1**	0.919*** (.25)	2.507	[1.543, 4.075]
	3 vs **1**	−1.246*** (.25)	0.288	[0.177, 0.468]
	4 vs **1**	−0.615** (.20)	0.541	[0.366, 0.799]
	5 vs **1**	0.847*** (.20)	2.332	[1.580, 3.442]
	3 vs **2**	−2.165*** (.32)	0.115	[0.061, 0.216]
	4 vs **2**	−1.534*** (.28)	0.216	[0.125, 0.372]
	5 vs **2**	−0.072 (.20)	0.930	[0.633, 1.366]
	4 vs **3**	0.631** (.23)	1.880	[1.199, 2.949]
	5 vs **3**	2.093*** (.29)	8.110	[4.635, 14.187]
	5 vs **4**	1.462*** (.23)	4.313	[2.739, 6.792]
Autonomy	2 vs **1**	0.497 (.33)	1.644	[0.860, 3.143]
	3 vs **1**	−0.118 (.19)	0.889	[0.608, 1.299]
	4 vs 1	−0.058 (.17)	0.944	[0.668, 1.334]
	5 vs 1	0.138 (.17)	1.148	[0.830, 1.590]
	3 vs **2**	−0.615 (.37)	0.541	[0.264, 1.108]
	4 vs **2**	−0.555 (.35)	0.574	[0.290, 1.137]
	5 vs **2**	−0.359 (.30)	0.698	[0.390, 1.252]
	4 vs **3**	0.060 (.19)	1.062	[0.734, 1.536]
	5 vs **3**	0.256 (.23)	1.292	[0.832, 2.006]
	5 vs **4**	0.196 (.20)	1.217	[0.828, 1.789]
Learning Opp.	2 vs **1**	−3.084*** (.61)	0.046	[0.014, 0.152]
	3 vs **1**	1.648*** (.30)	5.198	[2.881, 9.379]
	4 vs **1**	0.965*** (.21)	2.626	[1.736, 3.972]
	5 vs **1**	−1.158*** (.20)	0.314	[0.211, 0.469]
	3 vs **2**	4.732*** (.69)	113.513	[29.318, 439.500]
	4 vs **2**	4.049*** (.66)	57.348	[15.831, 207.747]
	5 vs **2**	1.926** (.56)	6.861	[2.286,20.590]
	4 vs **3**	−0.683* (.29)	0.505	[0.289, 0.883]
	5 vs 3	−2.806*** (.34)	0.060	[0.031, 0.117]
	5 vs 4	−2.123*** (.27)	0.120	[0.071, 0.201]

Note. Learning Opp. refer to learning opportunities. Profile 1 = average profile; Profile 2 = burned out, cynical and bored profile; Profile 3 = engaged profile; Profile 4 = relatively engaged profile; Profile 5 = relatively burned out, cynical and bored profile.

Table 7. Results from predictive analysis in Sample 2 - predictors of the profiles.

Predictor variable	Compared profiles	Coeff (SE)	Odds ratio	95% CI
Cognitive demands	2 vs **1**	−0.834** (.31)	0.434	[0.237, 0.794]
	3 vs **1**	−0.549* (.25)	0.577	[0.352, 0.946]
	4 vs **1**	−0.730** (.28)	0.482	[0.280, 0.830]
	5 vs **1**	−0.628* (.32)	0.534	[0.285, 1.000]
	3 vs **2**	0.285 (.24)	1.329	[0.834, 2.119]
	4 vs **2**	0.104 (.21)	1.109	[0.729, 1.687]
	5 vs **2**	0.206 (.25)	1.229	[0.757, 1.997]
	4 vs **3**	−0.181 (.20)	0.834	[0.560 1.244]
	5 vs **3**	−0.078 (.25)	0.925	[0.572, 1.494]
	5 vs **4**	0.103 (.27)	1.108	[0.656, 1.872]
Role conflict	2 vs **1**	−2.391*** (.36)	0.092	[0.045, 0.186]
	3 vs **1**	−0.490 (.27)	0.613	[0.363, 1.035]
	4 vs **1**	−1.740*** (.30)	0.176	[0.098, 0.316]
	5 vs **1**	−0.576 (.34)	0.562	[0.291, 1.087]
	3 vs **2**	1.901*** (.32)	6.692	[3.547, 12.623]
	4 vs **2**	0.651* (.28)	1.917	[1.105, 3.327]
	5 vs **2**	1.815*** (.33)	6.140	[3.221, 11.706]
	4 vs **3**	−1.250*** (.25)	0.287	[0.176, 0.466]
	5 vs **3**	−0.086 (.30)	0.918	[0.506, 1.664]
	5 vs **4**	1.164*** (.30)	3.202	[1.772, 5.785]
Autonomy	2 vs **1**	−1.011** (.34)	0.364	[0.187, 0.710]
	3 vs **1**	−0.112 (.26)	0.894	[0.537, 1.488]
	4 vs **1**	−0.481 (.31)	0.618	[0.336, 1.138]
	5 vs **1**	−0.624 (.32)	0.536	[0.285, 1.009]
	3 vs **2**	0.898** (.28)	2.455	[1.424, 4.234]
	4 vs **2**	0.529* (.24)	1.698	[1.059, 2.722]
	5 vs **2**	0.387 (.26)	1.472	[0.886, 2.445]
	4 vs **3**	−0.369 (.24)	0.692	[0.431, 1.111]
	5 vs **3**	−0.511* (.24)	0.600	[0.372, 0.967]
	5 vs **4**	−0.143 (.25)	0.867	[0.528, 1.425]
Learning Opp.	2 vs **1**	3.812*** (.47)	45.235	[18.088, 113.123]
	3 vs **1**	1.728*** (.33)	5.632	[2.961, 10.710]
	4 vs **1**	2.880*** (.43)	17.821	[7.701, 41.240]
	5 vs **1**	3.133*** (.47)	22.935	[9.155, 57.457]
	3 vs **2**	−2.084*** (.34)	0.124	[0.064, 0.243]
	4 vs **2**	−0.932** (.32)	0.394	[0.213, 0.730]
	5 vs **2**	−0.679* (.33)	0.507	[0.264, 0.972]
	4 vs **3**	1.152*** (.30)	3.164	[1.761, 5.686]
	5 vs **3**	1.404*** (.32)	4.072	[2.167, 7.654]
	5 vs **4**	0.252 (.34)	1.287	[0.661, 2.506]

Note. Profile 1 = burned out, cynical and bored profile; Profile 2 = engaged profile; Profile 3 = relatively burned out, cynical and bored profile; Profile 4 = averagely bored and engaged profile; Profile 5 = engaged, exhausted and emotionally impaired profile.

conflict increased the probability of belonging to Profile 1 (*average profile)* compared to Profile 3 (*engaged profile*), and 4 (*relatively engaged profile)*. In Sample 2, higher levels of role conflict were associated with an increased likelihood of belonging to Profile 3 *(relatively burned out, cynical, and bored)* and Profile 5 *(engaged, exhausted, and emotionally impaired)* compared to Profiles 2 *(engaged)* and 4 *(averagely bored and engaged)*. Similarly, higher levels of role conflict increased the probability of belonging to Profile 4 *(averagely bored and engaged)* compared to Profile 2 *(engaged)*.

Results concerning autonomy did not support our Hypothesis 7a, which stated that autonomy would predict membership in profiles characterized by low burnout, boredom and high work engagement. In fact, in Sample 1, no significant result was found in support of this hypothesis. Moreover, in Sample 2, higher autonomy increased the likelihood of belonging to Profile 1 *(burned out, cynical, and bored)* compared to Profile 2 *(engaged)* as well as to Profile 3 *(relatively burned out, cynical, and bored)* compared to Profiles 2 *(engaged)* and 5 *(engaged, exhausted, and emotionally impaired)*. Autonomy also increased the probability of belonging to Profile 4 *(averagely bored and engaged)* compared to Profile 2 *(engaged)*.

Consistently with Hypothesis 7b, in both samples, learning opportunities predicted membership in profiles characterized by lower boredom. In Sample 1, the analysis showed that higher learning opportunities increased the probability of belonging to Profile 5 (*relatively burned out, cynical and bored)* compared to Profile 2 (*burned out, cynical and bored profile)*. Moreover, higher learning opportunities increased the probability of belonging to Profile 4 (*relatively engaged profile)* compared to Profile 1 (*average profile)*, to Profile 2 (*burned out, cynical and bored profile)* and to Profile 5 (*relatively burned out, cynical and bored)*. Then, higher learning opportunities have shown to increase the probability of belonging to Profile 3 (*engaged profile*) compared to all the other profiles. Finally, higher learning opportunities increased the probability of belonging to Profile 1 (*average profile*) compared to Profile 2 (*burned out, cynical and bored profile*, and 5 (*relatively burned out, cynical and bored)*. In Sample 2, higher learning opportunities, increased the likelihood of belonging to Profile 2 *(engaged)* compared to all other profiles. Learning opportunities also increased the probability of belonging to Profile 3 *(relatively burned out, cynical, and bored)* compared to Profile 1 *(burned out, cynical, and bored)*, and of belonging to Profile 4 *(averagely bored and engaged)* compared to Profiles 1 *(burned out, cynical, and bored)* and 3 *(relatively burned out, cynical, and bored)*. Finally, learning opportunities increased the likelihood of belonging to Profile 5 *(engaged, exhausted, and emotionally impaired)* compared to Profiles 1 *(burned out, cynical, and bored)* and 3 *(relatively burned out, cynical, and bored)*.

Discussion

The present research aimed to investigate the co-occurrence of job boredom, burnout, and work engagement, as well as their links with job demands and resources using a person-centred longitudinal approach in two samples. We identified multiple well-being profiles – each defined by distinct combinations of boredom, burnout, and engagement – and assessed their temporal stability and links with job demands and resources. Our results demonstrate that boredom, burnout, and engagement co-occur in complex patterns, confirming established models and uncovering new dynamics in how boredom relates to burnout and engagement over time. This extends previous literature by offering a more detailed mapping of how these constructs interact longitudinally, beyond static relations.

Several key findings were replicated across Sample 1 and Sample 2 – using different measurement scales for boredom and burnout constructs – thus reinforcing their robustness. In both studies at least one profile emerged with high work engagement and low job boredom and burnout dimensions, and another with low engagement and high boredom and burnout scores. This confirmed the presence of traditional profiles in line with the Warr (1990) model of well-being, adapted by Harju and colleagues (2014), which conceptualizes boredom and burnout as distinct yet interrelated constructs, positioned at the opposite end of the well-being spectrum from engagement. However, beyond those traditional profiles, both samples revealed intermediate well-being profiles that underscore the multidimensional nature of workplace experience.

Findings from Sample 1 highlighted profiles characterized by low levels of burnout and job boredom and high levels of work engagement, although showing different intensities. Moreover, the identification of a profile with moderate levels of job boredom, burnout, and engagement confirms that these states are not always experienced in extreme forms. Notably, in Sample 2, a profile characterized by relatively high job boredom, above-average burnout, and below-average engagement suggests that boredom and burnout might exist along a spectrum rather than as distinct categories. This supports research suggesting that well-being at work is multidimensional and does not always fit into binary engaged-vs.-burned-out distinctions (Timms et al., 2012).

The findings also support the idea that boredom and burnout are highly intertwined experiences. Following Martela's (2025) theoretical framework and concerning the overlap between constructs in perceived well-being, it is plausible to consider, on the one hand, that the conative experience of burnout might be tinged with the affective experience of job boredom. On the other hand, these findings strengthen the idea that the affective experience of job boredom may be closely associated with more stable conative negative well-being states such as burnout. The results of this study also highlighted a strong link between boredom and cynicism in the two samples through the coexistence of job boredom and cynicism in multiple profiles. When looking closely at the burnout configurations and job boredom in the profiles found in both samples, levels of job boredom and cynicism exhibit similar levels and patterns. Particularly the observed combination of low boredom with exhaustion shows that boredom and exhaustion can diverge. When burnout dimensions are considered, job boredom is more closely tied to cynicism than to other burnout dimensions. These results may indicate that job boredom is more strongly tied to the cognitive and meaning-related dimensions of burnout (e.g., detachment) than to its emotional or energetical components, and highlights cynicism as the key burnout facet to examine in relation to job boredom, echoing earlier evidence of their close association (e.g., Toscanelli et al., 2024; Westgate & Wilson, 2018).

In some instances, the results did not confirm our expectations. A profile characterized by high burnout and work engagement and low job boredom did not consistently appear across samples. This challenges previous findings suggesting that employees can be simultaneously highly engaged and exhausted (e.g., Salmela-Aro et al., 2019). However, in Sample 2, a profile emerged with relatively high work engagement, relatively high exhaustion and emotional impairment, but relatively low boredom, thus adding evidence to the literature showing that work engagement and exhaustion can co-exist (Salmela-Aro et al., 2019). This suggests that some employees remain engaged despite experiencing emotional strain, and that engagement and exhaustion can co-exist under certain conditions, especially when employees remain highly invested in their work (Timms et al., 2012). The absence of this profile in Sample 1 may suggest that exhaustion may be more of a limiting factor for engagement in shorter-term studies, while over longer periods, engagement and exhaustion may co-develop in certain workers, in line with longitudinal evidence indicating that engagement can be sustained over time alongside exhaustion (Lehtiniemi et al., 2024).

Regarding the within-sample and within-person stability of profile configurations, the five-profile solution identified at each measurement point was stable and interpretable, confirming that different well-being experiences at work persist over time. In both samples, within-sample stability has been confirmed, in line with the existing literature (Harju et al., 2023; Lehtiniemi et al., 2024). While burnout and work engagement have shown stability over time in other studies (e.g., Mäkikangas et al., 2016), our study extends these findings by supporting the idea that although job boredom is a transient experience at its core, it can be a stable experience. However, for profiles with similar shapes but different levels of intensities the transitions from one profile to another were high (around 75%), suggesting that employees might experience a change in the intensity of these experiences but not in the pattern. Interestingly, for a minority in Sample 2 a transition from the averagely bored and engaged profile towards the burned-out, cynical, and bored profile was observed. This advances our understanding of job boredom by suggesting that moderate boredom can, over time, develop into more severe disengagement if left unaddressed. These findings further confirm that job boredom should not be dismissed as a temporary or insignificant experience but rather as a psychological state that may escalate into more serious well-being negative states, thus adding evidence to the current literature on this topic (e.g., Harju et al., 2023)

Finally, in both samples, role conflict was strongly associated with profiles characterized by burnout and boredom. This aligns with prior research showing that hindering demands fuel disengagement and mental exhaustion and contribute to both burnout and boredom (Demerouti & Bakker, 2023; Harju et al., 2023). However, unexpectedly, in both samples, cognitive demands increased the probability of belonging to the burned-out, cynical, and bored profile rather than the engaged profile. This contradicts the assumption that challenge demands may reduce boredom (Harju et al., 2023). Instead, it suggests that certain challenge demands may become overwhelming, leading employees to experience both stress and detachment from work, in line with the Job Demands-Resources model (JD-R, Bakker & Demerouti, 2007; Schaufeli & Bakker, 2004) positively linking job demands and strain and corresponding new developments on the challenge-hindrance stressors framework (see Podsakoff et al., 2023). Finally, following the literature (Demerouti & Bakker, 2023; Rošková & Faragová, 2020), challenge stressors should relate positively to both strain and engagement at the same time. The results of our study do not confirm this assumption. Higher cognitive demands increased the probability of belonging to profiles characterized by high levels of burnout but not to profiles characterized by high engagement in both samples. This contributes to the literature by challenging assumptions related to challenge and hindrance demands (e.g., Demerouti & Bakker, 2023).

Results concerning job resources were mostly as expected, in both samples. Learning opportunities predicted membership in the engaged profile and the relatively engaged profile, confirming their protective role against boredom (Reijseger et al., 2013; Toscanelli et al., 2021). However, in Sample 2, higher autonomy was associated with boredom-related profiles rather than engagement, suggesting that autonomy alone is insufficient to prevent boredom. In fact, autonomy without sufficient challenge-related resources may leave employees solely responsible for structuring their work, which may increase a sense of understimulation. This finding supports the idea, in line with previous studies (Toscanelli et al., 2021), that resources providing stimulation and developmental opportunities may be more effective in counteracting boredom than autonomy. Notably, learning opportunities were also linked to the relatively burned-out and emotionally impaired profile, indicating that even beneficial resources may not fully prevent exhaustion in demanding work environments. Particularly, this result suggests that resources fostering learning and competence development may entail cognitive and emotional investment. While such resources stimulate personal growth and development (Demerouti et al., 2001), they may simultaneously involve sustained mental effort, which can contribute to exhaustion in demanding work contexts. This pattern underscores that learning opportunities can be protective against boredom while co-occurring with strain-related outcomes.

In sum, the present research makes several contributions to the literature on work-related well-being. First, by adopting a longitudinal person-centred approach, this study advances understanding of job boredom by demonstrating how it co-occurs with burnout and work engagement in distinct and stable well-being configurations over time. In doing so, it clarifies the conceptual positioning of job boredom within broader well-being frameworks, highlighting its close alignment with cynicism and mental distance rather than with exhaustion alone. Second, the identification of multiple longitudinal profiles and their transitions extends existing research by showing that boredom, burnout, and engagement can combine in nuanced ways that primarily vary in intensity rather than in qualitative pattern and supports a holistic view of workplace well-being. Finally, by examining job demands and resources as predictors of profile membership and transitions, this study provides a more fine-grained application of the Job Demands-Resources model, illustrating how different types of demands and resources are associated with favourable and unfavourable combinations of well-being states over time. Taken together, these findings extend an integrative and dynamic perspective on work-related well-being.

Limitations and future research directions

While our study provides novel insights, it also has limitations that future research should address. Although the use of LTA across two samples provides valuable insights into within-person stability and change in latent profiles, several limitations should be noted.

First, our study is based on two convenience samples. Future research should seek to replicate these profile transitions in more representative samples to determine the extent to which profile structures and transition probabilities are replicable. Second, the time gap between measurements in our two samples may have limited our ability to detect more immediate or short-term changes in the constructs of interest. This is important in the context of work and well-being research, where fluctuations in job demands, resources, and employee states (e.g., stress, engagement, affect) can occur due to dynamic organizational environments (Bakker & Demerouti, 2017; Sonnentag et al., 2025). Future studies should incorporate additional measurement waves – ideally with shorter lags – to capture finer-grained temporal dynamics. Third, our study focuses on a very narrow range of contextual factors. Future research can expand this to understand how other important factors related to work well-being (e.g., social support, variety, job insecurity) (De Witte, 2005; Demerouti et al., 2001) might contribute to the stability and emergence of profiles. Moreover, because we adopted a person-centred approach, we used a one-dimensional score for work engagement to avoid imbalance with boredom, which is also measured on a unidimensional scale. Future research could, however, examine the distinct dimensions of work engagement (vigour, dedication, and absorption) to capture its multidimensional nature and explore whether these facets differentially relate to boredom. Another limitation of the present study is that it focused on antecedents of well-being profiles but did not examine their potential consequences. As such, we did not investigate whether membership in, or transitions between, different well-being profiles were associated with important work-related outcomes such as job performance, turnover intentions, absenteeism, or health-related indicators. Examining such outcomes would be a valuable direction for future research, as it would allow for a more comprehensive assessment of the functional implications of different boredom-burnout-engagement configurations and their evolution over time. Finally, this study did not include trait-like individual differences, such as personality traits (e.g., neuroticism, conscientiousness) or trait-like variables such as boredom proneness (Farmer & Sundberg, 1986). These characteristics are known to affect how individuals perceive and react to their work environments (e.g., Bakker et al., 2010) and could play a key role in shaping profile membership and transitions over time. Future research should incorporate such dispositional factors to advance theory on individual differences in work-related well-being.

Practical implications

From an organizational perspective, these findings underscore the need for tailored interventions. While boredom emerges as a critical risk factor that can persist over time and co-occur with burnout, the identified profiles indicate that boredom, burnout, and engagement could be addressed jointly. Organizations should therefore not only focus on reducing exhaustion, but also on designing work that remains meaningful and stimulating, while supporting sustained engagement. Moreover, our results showed that employees in moderately bored and engaged profiles could transition into burned-out and cynical profiles over time. This highlights the need for early intervention strategies, such as job crafting and autonomy-supportive leadership, to prevent the escalation of boredom into severe disengagement. In line with the Job Demands-Resources model (Bakker & Demerouti, 2017), our findings further indicate that hindering job demands, such as role conflict, are systematically associated with unfavourable well-being profiles characterized by burnout and boredom. Organizations should therefore pay particular attention to identifying and managing these demands so that they do not accumulate and undermine employee well-being. At the same time, the presence of profiles combining high engagement with elevated strain suggests that highly engaged employees may still be at risk of exhaustion, underscoring the importance of monitoring workload and recovery even among engaged workers. Finally, our findings highlight the benefits of growth-related job resources (such as learning opportunities). Fostering these resources could thus serve as a tool for reducing job boredom and thereby promoting workplace well-being. However, their association with profiles involving exhaustion suggests that such resources should be implemented alongside adequate support and manageable demands. Together, these findings suggest that effective interventions should aim to balance stimulation, development, and recovery to foster sustainable engagement and prevent both boredom and burnout.

Conclusion

This study offers evidence for the dynamics of job boredom, burnout, and engagement over time. Using a person-centred longitudinal approach, we showed that job boredom is not merely the absence of engagement, but a distinct and enduring psychological state with important implications for employee well-being. Our findings highlight the need for a more differentiated perspective on workplace well-being-one that recognizes boredom and burnout as coexisting yet distinct risks to sustained engagement and well-being. Notably, the consistent alignment of job boredom with the cynicism dimension of burnout points to a meaningful conceptual co-existence that warrants further exploration. While job demands and resources generally conformed to theoretical expectations, exceptions – such as the complex role of job autonomy – suggest that certain resources may not uniformly buffer against strain. These insights deepen our understanding of work-related psychological states and inform the development of targeted interventions to promote employee well-being.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study are available from the corresponding author, Cecilia Toscanelli, upon reasonable request.

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