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Beyond the flow continuum: A person-centered approach to identify unique constellations of flow components

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ABSTRACT

Not all psychological states experienced during work are equally rewarding, yet little is known about what sets particularly rewarding states apart from others. Flow is a highly rewarding state of deep absorption in which actions feel effortless and automatic. Although originally conceptualized as a discrete, all-or-nothing state, flow is now often treated as varying in degree across daily work activities. This shift risks blurring the boundaries between flow and other psychological states, leading to conceptual confusion, imprecise theoretical frameworks, and inconsistent research practices. To address this ambiguity, our study provides a clear empirical test of the nature of flow by identifying unique patterns of its core components that set it apart from other psychological states. In a day reconstruction study involving 199 employees (2927 observations), multilevel factor mixture analysis yielded six distinct state profiles: Deep Flow, Microflow, Apathy, Boredom, Arousal, and Anxiety. Two profiles theoretically aligned with the concept of flow: one with peak scores on absorption, effortless control, and intrinsic reward (i.e., Deep Flow), and one with moderately high scores on the three components (i.e., Microflow). Both emerged during 29% and 44% of the activities, respectively, and particularly when activities were scored high on challenge appraisal or low on hindrance appraisal. These findings clarify the nature of flow by empirically demonstrating its distinctiveness from other states, thereby resolving a key ambiguity and advancing flow theory and research.

1. Introduction

Imagine being fully immersed in a work activity where nothing else matters, and time seems to disappear. After a while, this state comes to an end. You have entered and exited what is known as flow, a state characterized by absorption, effortless control, and intrinsic reward (Csikszentmihalyi, 1990; Norsworthy et al., 2021). This rewarding state fulfills basic psychological needs for mastery and sparks interest and motivation to engage in challenging work activities (Csikszentmihalyi, 2000, 2004). The integration of flow

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into theoretical frameworks such as Social Cognitive Theory (Bandura, 2001) helps explain its relevance for vocational outcomes by conceptualizing flow as a motivational state that benefits long-term career growth, employability, and sustainable careers (e.g., Nash, 2024; Salanova et al., 2006; Van der Heijden & Bakker, 2011). In line with this perspective, research has shown that flow contributes to health, performance, and motivational outcomes (Aust et al., 2022; Kasa & Hassan, 2013). Although evidence in vocational research clearly points to the importance of flow states in daily work life (for a meta-analysis, see Liu et al., 2023), the extent to which flow is conceptually distinct from other psychological states remains unclear (Fullagar et al., 2017).

Specifically, with the rise of experience sampling methods (e.g., Gabriel et al., 2019; Sonnentag et al., 2025), vocational research has increasingly focused on when and why distinct psychological states, such as boredom, arousal, and flow, emerge in daily work life (Navarro et al., 2022; Podsakoff et al., 2019). Despite this progress, most empirical studies conceptualize these states as continuous constructs, paying limited attention to their potential discrete nature or to how different constellations of their components may form qualitatively distinct states (Hofmans et al., 2020; Spurk et al., 2020). For example, although flow was originally described as a discrete, peak state that occurs infrequently (e.g., Bakker, 2005), it is now typically operationalized as a continuous construct, implicitly assuming that it varies along a single continuum from low to high levels of flow (Schiepe-Tiska & Engeser, 2017). Conceptually, however, one might argue that low flow scores are phenomenologically different from peak flow scores (Csikszentmihalyi, 1990). Moreover, rather than representing weaker instances of the same state, different constellations of the core flow components may reflect qualitatively distinct states altogether. For example, effortless control combined with low absorption and intrinsic reward may indicate boredom (Massimini et al., 1987). Despite such nuances, the shift from conceptualizing flow as a discrete peak state to treating it as a continuous construct appears to be driven largely by the practical convenience of calculating a single global flow score for measurement and analysis (Moneta, 2021). This continuous approach, however, risks conflating flow with other psychological states, which may in turn lead to imprecise theoretical models and or biased empirical findings, ultimately constraining our understanding of the nature, predictors, and outcomes of flow.

To provide insights into the very nature of flow, we conducted a day reconstruction study in which we sampled 2927 work states from almost 200 employees. Drawing on those data, we first tested to what extent distinct daily psychological states are characterized by unique within-person constellations (or state profiles) of absorption, effortless control, and intrinsic reward (i.e., the core components of flow). Apart from examining the extent to which those unique within-person state profiles theoretically correspond with the concept of flow, we also investigated their overlap with discrete flow states as measured by the Flow Questionnaire (FQ) (Csikszentmihalyi & Csikszentmihalyi, 1988). To further illuminate the meaning of these distinct constellations of flow component scores, we examined how frequently they occurred within individuals, enabling the exploration of individual differences in the occurrence patterns of flow and non-flow states. Finally, building on prior research that draws on stress and motivational theories to predict flow (Demerouti & Mäkikangas, 2017; Peifer & Wolters, 2021), we examined how employees' appraisal of work activities as challenging or hindering related to unique constellations of flow component scores.

By doing so, this study makes several contributions to the literature on work-related flow. First, we provide an empirically established taxonomy of psychological states based on unique constellations of the flow components, examining how flow may be distinct from other states that differ in level (e.g., low scores on all three flow components) or shape (e.g., different constellations of scores on the three flow components). As such, this study responds to longstanding calls to clarify the core nature of flow and how it differs from other states (Fullagar & Kelloway, 2013), while also contributing to broader efforts within vocational research to understand whether psychological states during daily work activities are inherently discrete or continuous in form (Fullagar et al., 2017).

Second, we shed light on individual differences in the occurrence of those distinct psychological states, enabling scholars to better understand the prevalence of flow and non-flow states. Because the core flow components enhance vocational outcomes (Van der Heijden & Bakker, 2011), and are strong indicators of sustainable careers (De Vos et al., 2020; Nash, 2024), understanding how often and which employees experience flow can inform career counseling practices and other strategies to optimize work design, work allocation, and tailored interventions (Bakker & van Woerkom, 2017; Dik et al., 2015; Robertson, 2018). Hence, we advance vocational research on between-person differences in the emergence of psychological states by identifying distinct groups of individuals based on the prevalence of these states, thereby offering a more comprehensive understanding of how such states unfold in daily work life (Spurk et al., 2020).

Third, we provide insights into the predictors that distinguish flow from non-flow states, advancing knowledge on the role of challenge and hindrance appraisals in the occurrence of work-related flow. In doing so, this study refines existing theoretical frameworks (Bakker & van Woerkom, 2017; Demerouti & Mäkikangas, 2017) by shedding light on how the appraisal of work activities, beyond the mere engagement in these activities, shapes psychological states during daily work life (e.g., Pluut et al., 2024; Webster et al., 2011). All in all, this study contributes to previous theoretical approaches that integrate stressor and motivational theories within flow research (Peifer & Tan, 2021; Peifer & Wolters, 2021), while also contributing to HRM policy-making and career counseling practices by shedding light on the occurrence of patterns of psychological states and the activities that foster their prevalence.

2. Theoretical background

2.1. The nature of flow

Numerous ambiguities have surrounded the core components and nature of flow (Abuhamdeh, 2020; Engeser et al., 2021; Schiepe-Tiska & Engeser, 2017). However, there is an increasing agreement that flow consists of three core components – absorption, effortless control, and intrinsic reward – all of which are required to experience flow (Norsworthy et al., 2021; Peifer & Engeser, 2021). If one component is absent (e.g., effortless control), scholars argue that individuals shift to a qualitatively distinct state, such as anxiety (Massimini & Carli, 1988). Thus, the actual occurrence of flow only happens when all three components are simultaneously and highly present. Despite this consensus, it remains unclear what separates flow from other states and, thus, whether flow is a discrete state that only emerges beyond a certain threshold or a continuous state with varying degrees from low to high levels (Abuhamdeh, 2020; Moneta, 2021).

One core reason for this ambiguity is that many scholars argue that flow states can fluctuate in intensity. Csikszentmihalyi (2000) described less intense flow states that can occur during daily activities as 'microflow', whereas he referred to 'deep flow' as states during which all three of the flow components are present at a peak level. Deep flow emerges when an intense challenge stretches one's skills, which requires individuals to direct all their attention and energy resources to cope with that challenge (Csikszentmihalyi, 1990). Microflow, in turn, is typically experienced as more relaxing than deep flow because the stakes and challenges are lower (Clarke & Haworth, 1994). Even though individuals are not (always) relaxed when being engaged in deep flow, its challenging nature typically results in increased productivity and fulfillment (Lambert et al., 2013).

Many scholars thus argue that flow fluctuates along a continuum of intensity (Ceja & Navarro, 2017). Adopting this perspective, scholars started using continuous measures to study flow (e.g., Bakker, 2008; Jackson & Eklund, 2002; Jackson & Marsh, 1996). This method entails assessing the intensity of the distinct flow components using 'extent' or 'agreement' response options (Delle Fave et al., 2011; Delle Fave & Bassi, 2023). By treating flow as a continuous rather than a discrete state and assuming that all states can be placed somewhere on this flow continuum, this approach avoids the challenges of distinguishing between flow and non-flow states (Abuhamdeh, 2020).

Although the continuous approach is elegant and has some practical advantages in terms of simplicity, it risks limiting our understanding of the nature and occurrence of flow. First, the assumption that all states vary in flow intensity may conflict with the idea that flow states only happen when all three components are simultaneously (highly) present. Indeed, when describing their flow states, individuals often refer to a "peak" state that feels different from merely being involved in an activity (Csikszentmihalyi, 2000). Moreover, individuals often perceive flow as having distinct start and end points, accompanied by a loss of time awareness (Csikszentmihalyi & Csikszentmihalyi, 1988). These descriptions suggest that flow is a peak, "all-or-nothing" state that individuals enter and exit. As such, operationalizing all states as varying in the intensity of flow may risk 'imposing' the term flow on non-flow states (Moneta, 2021). Recently, Peifer and Engeser (2021) proposed a combination of the discrete and continuous conceptualizations, acknowledging that, while a certain threshold may separate flow from non-flow, flow states can still vary in intensity once that threshold is exceeded. However, to date, there is no empirical evidence supporting this conceptualization of flow (Norsworthy et al., 2021).

Second, the practice of calculating a global flow score ignores that shape (or configurational) differences in the core flow components may also differentiate flow and other psychological states. When the three flow components are combined into a global score, a peak score on one component can be compensated for by a (very) low score on the other two components (Norsworthy et al., 2023). For example, whereas the global score would indicate a moderate level of flow, scoring high only on effortless control may yield a phenomenologically distinct state (e.g., boredom), as individuals do not feel absorbed or rewarded during such an activity. Likewise, the absence of just one component, when the other two components are highly present, might result in a state that differs fundamentally from flow but scores relatively high on the continuum. For example, arousal may arise when individuals are highly absorbed and in control but lack a sense of reward in their activity (Massimini et al., 1987). This state may differ qualitatively from (deep) flow, as the absence of control leaves individuals feeling unfulfilled and strained.

2.2. *Distinguishing flow from other states*

Understanding which distinct psychological states emerge during work is essential, as it helps scholars to grasp during which activities individuals tend to experience flow and how they shift between non-flow states (Bassi & Delle Fave, 2012; Fullagar et al., 2017). Initially, flow scholars assumed that the occurrence of all psychological states depends on two factors: the challenges posed by the ongoing activity and the level of skill required to cope with those challenges (e.g., Moneta & Csikszentmihalyi, 1996, 1999). Drawing on the Flow Quadrant Model (FQM), scholars initially distinguished four discrete states: flow (high challenge and high skill), anxiety (high challenge and low skill), boredom (low challenge and high skill), and apathy (low challenge and low skill) (e.g., Csikszentmihalyi & LeFevre, 1989). This approach was later refined in the Experience Fluctuation Model (EFM) to provide a more refined taxonomy distinguishing eight distinct psychological states, which, besides flow, also include control, arousal, worry, and relaxation (Massimini et al., 1987).

According to the FQM and EFM, flow occurs when challenge and skill are balanced at a high level (Moneta, 2021), a condition that is strongly related to greater excitement, enjoyment, creativity, happiness, and interest (e.g., Clarke & Haworth, 1994; Haworth & Evans, 1995; Haworth & Hill, 1992). The state of control arises when individuals are moderately challenged, yet feel highly skilled in coping with these challenges, giving a sense of mastery, albeit to a lesser extent than flow (Massimini et al., 1987). However, according to this taxonomy, too much control from low challenges or high skill usage leads to individuals disengaging from their activity. For instance, boredom emerges when individuals do not feel triggered to perform their activity because of its low challenges and moderate levels of skill requirement. Relaxation, by contrast, is a state characterized by low cognitive investment and a feeling of ease during an unchallenging activity because even though skills are required, individuals' current skill levels largely exceed the activity's challenges (Clarke & Haworth, 1994).

More negative states emerge when individuals do not feel in control while being too challenged. Arousal occurs when challenges are high and slightly exceed individuals' skills. This state is triggered by effort and tension, although it still creates excitement due to the challenges of the situation (Massimini & Carli, 1988). Anxiety is marked by distress and tension regarding one's ability to cope with highly challenging activities, while worry emerges when challenges are moderate, yet exceeding skills, leading to self-doubt and unease with little intrinsic reward (Delle Fave et al., 2011). Finally, apathy is a state of full disengagement and indifference that occurs when individuals do not feel challenged or motivated to use their skills (Delle Fave & Massimini, 2005).

Whereas the EFM is designed to offer a comprehensive overview of individuals' daily psychological states (Massimini et al., 1987), scholars have raised questions about its potential to accurately do so (e.g., Løvoll & Vittersø, 2014; Voelkl & Ellis, 1998). First, the EFM starts from combinations of challenges and skills rather than from actual states. By using such a predefined categorization, spurious profiles can emerge that may not accurately match states in daily life. Second, although this model treats challenges and skills as components of flow, they do not inherently produce flow for all individuals or in all situations. Whether they result in flow depends, for a relevant part, on the subjective importance of the activity (Engeser & Rheinberg, 2008). Thus, it is more accurate to conceptualize challenges and skills as predictors of flow rather than as flow components.

Finally, the EFM provides little clarity regarding the extent to which flow states can vary in intensity. In particular, the terms 'ease' (Clarke & Haworth, 1994) and 'moderate flow' (Haworth & Evans, 1995) were coined to describe moderately intense flow states, showing overlap with the concept of microflow (Csikszentmihalyi, 2000). However, most scholars using the EFM do not rely on this categorization and ignore potential level differences between peak and moderately intense flow states (Lambert et al., 2013; Løvoll & Vittersø, 2014; Torales et al., 2016). For these reasons, scholars began measuring the core components of flow to compute a global flow score and examine flow intensity levels, despite the previously mentioned drawbacks of this approach and the conceptual issues it introduces.

An alternative approach to arrive at a taxonomy would be to look for unique constellations (or profiles) of scores on the core flow components in an inductive (bottom-up) manner. Unfortunately, however, such research is currently lacking. This study addresses this issue by repeatedly measuring employees as they engage in their daily work activities, after which we identify unique profiles of scores on the core flow components using a person-centered approach (Spurk et al., 2020). Thus, rather than assuming that all states vary on a single flow continuum, person-centered techniques allow for the possibility that some constellations might reflect qualitatively distinct states (Woo et al., 2018). This means that the distinct psychological states are not based on assumed theoretical combinations of challenge and skills. Instead, profiles identified by person-centered techniques will emerge as unique constellations of the core flow components.

Given the high correlations between the flow components (Norsworthy et al., 2023), we expect at least three distinct state profiles to emerge, characterized by consistently low, moderate, or peak levels across all three flow components. Deep flow would theoretically correspond to the profile showing the highest levels across all core flow components (Csikszentmihalyi, 2000), while a profile characterized by moderate levels across the core flow components would correspond with the concept of microflow. Moreover, unique constellations that differ in quality (i.e., shape) may also emerge when employees score high on only one of the flow components (e.g., high effortless control), suggesting a distinct state (e.g., boredom). Additionally, whereas later extensions of the EFM operationalized eight distinct states (e.g., Massimini et al., 1987), studies using this taxonomy found several of those states to be rather infrequent (Bassi & Delle Fave, 2012; Lambert et al., 2013), suggesting a potential overlap or redundancy of these states. As such, our first hypothesis reads:

Hypothesis 1. There exist multiple state profiles among the flow components (absorption, effortless control, intrinsic reward), based on level (i.e., low, moderate, peak) and shape differences (i.e., unique constellations).

To gain a deeper understanding of these profiles, we will test to what extent they overlap with discrete flow states as measured by the Flow Questionnaire (FQ; Csikszentmihalyi & Csikszentmihalyi, 1988). The FQ identifies flow states – but not (unique constellations of) the flow components – by providing employees with flow quotes and asking them if they experienced a similar feeling (yes or no). Thus, assessing the overlap between the different constellations of the flow components and flow states identified by the FQ helps to further understand the state profiles.

2.3. The prevalence of (flow) states at work and individual differences therein

If certain state profiles occur frequently, whereas others rarely do, this helps in understanding how those states unfold in daily life (Clarke & Haworth, 1994; Csikszentmihalyi & LeFevre, 1989). However, because scholars have rarely studied how flow differs from non-flow states, it remains unclear how frequently employees experience different constellations of the three flow components. Studying the prevalence of distinct profiles could help scholars understand whether state profiles that theoretically align most closely with the deep flow concept (i.e., those with peak flow scores) are rare or more common. To this end, we will investigate the prevalence of state profiles in daily work life.

Flow might not occur during each work activity, as it requires specific conditions to emerge (e.g., Bartholomeyczik et al., 2024; Ilies et al., 2017). Employees typically only experience flow when they feel triggered by – and are completely focused on – their ongoing activity (Nakamura & Csikszentmihalyi, 2002). Research indicates that employees spend a substantial portion of their workdays on activities that are neither challenging nor motivating (e.g., emails, unstimulating meetings, administrative work) (Bakker & Oerlemans, 2019; Oerlemans & Bakker, 2018). Thus, only a handful of work activities are challenging and motivating enough for employees to potentially experience peak levels of the flow components (Ceja & Navarro, 2011, 2012). Despite limited empirical evidence on the prevalence of flow in daily work life, this suggests that the core flow components are not often simultaneously triggered to a peak level. For these reasons, we propose the following hypothesis:

Hypothesis 2. Profiles with low or moderate levels on the flow components are more prevalent at work than profiles with peak levels on the flow components.

Apart from studying the prevalence of state profiles during daily work activities at the within-person level, we will study differences in the prevalence of those profiles between employees at the individual level. Because most research considers flow as a state that all employees have (to some extent) during each activity (e.g., Liu et al., 2023), between-person differences in the prevalence of flow are often overlooked. Nevertheless, there are strong indications for the existence of such differences (Peifer & Wolters, 2021). Previous research has shown that some employees are characterized by an "autotelic personality" or "flow proneness" (Tse et al., 2020; Ullén et al., 2012), referring to the tendency to seek out challenging activities and experience flow (Csikszentmihalyi, 1990). Despite the existence of such personality traits, many employees do not associate flow with work-related activities or never experience flow during work at all (e.g., Bassi & Delle Fave, 2012; Moneta, 2012). The reason for these different occurrence patterns is that stable characteristics related to employees' jobs or work environments might repeatedly prevent or facilitate the state of flow (Bakker & van Woerkom, 2017; Demerouti & Mäkikangas, 2017).

Based on these insights, research has established that individual differences exist in the prevalence of flow states (Liu et al., 2023). However, it remains unclear how such individual differences take shape. This knowledge is important, as it helps in understanding how often flow states unfold in daily life and how employees shift between flow and non-flow states. Studying such individual differences also provides a deeper understanding of the nature and patterns of occurrence of employees' daily psychological states at work. Based on the assumption that some employees are more likely to experience flow at work (Csikszentmihalyi, 1990), we can assume peak levels of the flow components will occur more frequently among certain employees than others. Moreover, as flow is challenging to experience at work, we expect that most employees rarely experience peak levels of flow in daily work activities. Hence, we will test the following hypothesis:

Hypothesis 3. Employees vary in how frequently they experience different constellations of the flow components.

2.4. Predictors of psychological states

Finally, we will examine predictors of the distinct state profiles identified by unique constellations of scores on the flow components. The core assumption is that flow occurs when employees are challenged by a useful and relevant activity, as they will feel triggered to put their attention and energy into it (Csikszentmihalyi, 1990). This theoretical approach aligns closely with the Challenge-Hindrance Stressors Framework (CHSF; LePine, 2022), which builds upon the core principles of the Transactional Model of Stress and Coping (TMSC; Lazarus & Folkman, 1984). Specifically, the motivational assumption of these theories reads that employees feel more motivated to perform challenging activities, in contrast to hindering activities, because challenges allow long-term growth and enable employees to obtain their career goals (Podsakoff et al., 2023).

Stressors are classified by these frameworks as challenging when they encourage employees to make progress on work activities and allow them to develop, or as hindering when they prevent or constrain employees from accomplishing work activities and further development (Cavanaugh et al., 2000). Both the occurrence of stressors and how they are appraised strongly depend on the activity at hand (Lazarus & Folkman, 1984). That is, some activities might be perceived as challenging by employees, whereas others are perceived as hindering. Additionally, how employees appraise the same activity might vary between days (Horan et al., 2020). Considering its activity-level focus and appraisal perspective, flow scholars previously used this theoretical approach to study how the presence of challenge and hindrance stressors triggers or hinders flow (e.g., Feng, 2022; Peifer & Zipp, 2019; van Oortmerssen et al., 2020).

However, these scholars have overlooked the critical role of appraisals. According to the TMSC, appraisals play a crucial role in employees' states during daily work activities (Folkman et al., 1986). Employees can appraise activities as challenging or hindering, depending on whether they have the right coping resources to deal with them (Lazarus & Folkman, 1984). As such, the motivational hypothesis of the CHSF states that employees are motivated to invest their coping resources into activities appraised as challenging, rather than activities that are appraised as hindering (LePine et al., 2005; Podsakoff et al., 2007). Research suggests that the appraisal of activities determines work-related states, and not merely performing these activities, as different types of activities are not always appraised similarly by employees (Stiglbauer & Zuber, 2018; Webster et al., 2011). Integrating this perspective into flow theory, Peifer and Tan (2021) argued that flow occurs after appraising an activity as challenging, and not as hindering, because employees will put their effort into and devote attention to that activity.

For these reasons, examining how challenge and hindrance appraisals of work activities differentiate flow from non-flow states will help scholars to better understand when unique constellations of flow components emerge at work. Moreover, prior research also showed that, when employees are exposed to both challenge and hindrance stressors simultaneously, the detrimental outcomes of stressors are most pronounced (e.g., Pearsall et al., 2009). Based on this line of research, scholars called for more research investigating interactions between challenge and hindrance stressors, although few answered this call (Podsakoff et al., 2023). As such, we can expect that peak flow levels will emerge when challenge appraisal is high and hindrance appraisal is low. For these reasons, we suggest the following hypotheses:

Hypothesis 4a. Challenge appraisal is positively related to the deep flow profile.

Hypothesis 4b. Hindrance appraisal is negatively related to the deep flow profile.

Hypothesis 4c. Challenge and hindrance appraisals interact to predict experience profile membership, such that high challenge appraisal is associated with the deep flow profile only when hindrance appraisal is low.

3. Method

3.1. Participants

This study focuses on white-collar employees because they perform a variety of work activities with varying levels of challenge and skill (Morgeson & Humphrey, 2006). We recruited participants via Prolific to gain access to employees across different countries, organizations, and sectors (Douglas et al., 2023). To ensure that participants clearly understood the flow items (Delle Fave & Bassi, 2023), English had to be their primary language. To promote high compliance, we only recruited full-time employees who were scheduled to work five days during the study and had the intention of completing at least six questionnaires during the study period. Participants also needed a 95% approval rating across at least 20 previous Prolific studies.

Initially, 282 participants opened the baseline questionnaire, and of these, 274 provided consent to participate in the study. We filtered out 35 interested participants because they did not meet the eligibility criteria. We finally invited 239 participants to the daily questionnaires. During the study, 35 participants (i.e., 14.64%) dropped out because they did not respond to any of the questionnaires. We excluded five more participants because they did not read the instructions carefully and thus failed to answer compliance checks, suggesting careless responses. As such, our final sample comprises 199 participants who provided data on at least one questionnaire.

The sample's median age and tenure were 38 years ($SD = 9.92$) and 5 years ($SD = 7.29$), respectively. Approximately half of all participants were female (51.8%), and the majority were residents of the UK (92%) or Ireland (5%). Participants were highly educated, with 62.3% holding a higher education degree, working in a variety of jobs such as administration (12.6%), finance or accounting (12.1%), operations (8.5%), IT (7%), education (6.5%), and sales or business development (6%).

3.2. Participant bias and missing data analyses

We examined participant bias and missing-data patterns by testing whether participation (i.e., participants vs dropouts) and compliance (i.e., the number of completed questionnaires) were related to the focal variables in this study (Stone et al., 2023). First, we found that women were more likely to take part in the study than men ($\chi^2 = 7.31, p < .05$), but not employees who experience less flow in their work ($t = -0.42$, $p = .67$) (see Supplementary Table 1). Second, non-compliant participants were younger than compliant participants ($t = 3.00$, $p < .01$), but did not differ in the prevalence ($t = 1.45$, $p = .08$) or intensity of flow states ($t = 1.18$, $p = .24$) during the data collection (see Supplementary Table 2). Third, we found that the number of questionnaires participants completed was only related to their age ($F = 2.36$, $p < .05$) and not the other focal constructs (see Supplementary Table 3). As such, there was no relationship between participation and compliance, as well as the frequency of work-related flow states. These results suggest that our sample did not suffer from participant bias concerning the frequency of flow states. We return to this point in the discussion.

3.3. Procedure

The present study involves a baseline questionnaire and a day reconstruction study over five consecutive working days (Monday to Friday). Participants could view the study description and pre-screening via Prolific on Thursday before the start of the study. After registering, we asked participants to read through the full procedure of the study and complete the baseline questionnaire containing the informed consent, job and demographic variables, and screening questions. After completing the final daily questionnaire, participants received a debriefing sheet outlining the study's purpose and background.

The day reconstruction study involved two daily questionnaires, sent at 11:30 a.m. and 4:30 p.m. We instructed participants to complete the questionnaires immediately before lunch and immediately after the end of their workday. The questionnaires closed at 1.30 p.m. and 6.30 p.m., respectively. On average, participants completed the lunchtime questionnaire at 12:21 p.m. and the afternoon questionnaire at 5:14 p.m. Completing the questionnaire took about 6 min. We paid £1 for each completed questionnaire in Prolific (i.e., baseline and daily questionnaires). Furthermore, participants could receive a bonus of £4 for completing at least seven questionnaires and an additional bonus of £3 for completing all questionnaires. As such, participants could earn a total of £18.

We designed the questionnaires using the day reconstruction method (Kahneman et al., 2004). Participants had to reconstruct their morning or afternoon by dividing it into work activities (excluding breaks, commuting, or personal activities). Afterwards, we instructed them to label each activity (e.g., working on project X, meeting with Y), and to write down their approximate beginning and ending times. In the following step, we only presented two randomly selected activities (or one if participants only performed one work activity) to reduce participant burden. To refresh their memories, we asked participants for each selected activity to indicate where they were, what they were working on (using a drop-down list), and whom they were with (Kahneman et al., 2004). In the final step, we presented the questions regarding participants' flow states and work appraisals for each selected activity.

In this study, participants could report on a total of 20 work activities (i.e., two activities in the morning and afternoon for five consecutive workdays). Participants completed 1606 questionnaires containing data on one (if they only completed one) or two work activities, yielding an overall questionnaire-level compliance rate of 80.80%. After excluding questionnaires that were completed twice or during which participants answered carelessly (i.e., giving the same response to all items or failing attention checks), 1582 individual questionnaires remained. Finally, we excluded activities during which participants were not working (e.g., commuting), yielding a total sample size of 2927 work activities.

On average, participants performed six work activities per day ($SD = 2.64$), which lasted 62 min on average ($SD = 49.37$). An overview of the activities and the scores on flow, the FQ, and challenge and hindrance appraisals can be found in Supplementary Table 4. Out of the 2927 reported activities, 22% were related to performing an individual analytical activity (e.g., working with data), 19% involved written communication (e.g., e-mails), 17% referred to formal meetings, 14% related to routine or bureaucratic work (e.g., admin), 12% involved planning or preparation, 6% involved conversations about work (e.g., discussion), 5% referred to giving or receiving training, and 5% referred to other activities (e.g., teaching, teambuilding, networking). Additionally, analytical and planning activities scored highest on the global flow score (i.e., 5.09 and 4.93, resp.) and the FQ (i.e., 0.51 and 0.43, respectively). Analytical activities and formal meetings were highly rated as challenging (3.51), whereas routine and bureaucratic activities were the most hindering (1.94 and 1.89, respectively).

3.4. *Measures*

Based on recommendations in the literature, we measured flow in two ways: as a discrete and as a continuous state (Norsworthy et al., 2021; Peifer & Engeser, 2021).

3.4.1. *Continuous flow measure – Psychological Flow Scale*

We assessed flow using all nine items from the recently developed Psychological Flow Scale (Norsworthy et al., 2023). Whereas there is consensus that flow consists of three core components, existing instruments often conflate flow with its predictors and outcomes by measuring them simultaneously (e.g., FSS-2; Jackson & Eklund, 2002) or by measuring only one or two components (e.g., FKS; Rheinberg et al., 2003). The only exemption is the recently developed Psychological Flow Scale (Norsworthy et al., 2023), which is based on the scoping review of Norsworthy et al. (2021) identifying three core flow components: absorption, effortless control, and intrinsic reward.

Participants were required to indicate to what extent the items reflected their experience during each selected activity. Example items are: “All my attention was on the activity” (i.e., absorption); “My actions flowed effortlessly” (i.e., effortless control); and “I found the experience rewarding” (i.e., intrinsic reward) (1 = strongly disagree, 7 = strongly agree). The within-person omega values were 0.90, 0.83, and 0.88 for absorption, effortless control, and intrinsic reward, respectively.

3.4.2. *Discrete flow measure – Flow Questionnaire*

We used the shortened version of the Flow Questionnaire to assess flow as a discrete state[1] (Moneta, 2021). This instrument is the only discrete measure that has been implemented and validated by flow scholars (Bartholomeyczik et al., 2024; Moneta, 2012). We provided three flow quotes (e.g., “My concentration was like breathing, I never think of it.”) and asked whether participants experienced a similar feeling during their selected work activity or not (yes or no). When participants indicated a positive response to the FQ, we asked several additional questions on flow to further understand how it occurs (Norsworthy et al., 2023).

First, we asked how often participants experienced flow during the activity (i.e., just once, on two or three occasions, multiple occasions). If the state occurred more than once, participants were required to answer the following questions concerning their longest flow state. Second, we asked how long the flow state lasted (e.g., less than 10 min, between 10 and 30 min). Third, we assessed the intensity of flow using the following item: “Referring back to this experience, how strongly did you experience it?” (1 = very weak – 7 = very strong). The descriptive statistics for these questions are presented in Supplementary Tables 5 and 6.

3.4.3. *Challenge and hindrance appraisal*

We measured challenge and hindrance appraisal using all six items from LePine et al. (2016). We adapted the items to assess how participants appraised their activities. Example items are: “Working on this activity helped me to grow at work” (challenge appraisal – 3 items) and “Working on this activity hindered my growth at work” (hindrance appraisal – 3 items) (1 = strongly disagree, 5 = strongly agree). Within-person omegas were 0.77 and 0.81 for challenge and hindrance appraisal, respectively.

3.5. *Analytical approach*

To identify unique constellations of scores on the core flow components, we performed two-level factor mixture analyses (FMA), with states nested within employees (Lubke & Muthén, 2005). We performed these analyses in Mplus version 8.10 (Muthén & Muthén, 2017). Factor mixture analysis is a person-centered technique combining factor analysis and latent profile analysis by simultaneously modeling continuous and categorical latent factors (Meyer & Morin, 2016). As flow consists of three components that are theoretically expected to be correlated (Norsworthy et al., 2023), the continuous latent factor in FMA allows modeling covariation between the indicator variables within each profile (e.g., Morin et al., 2011). In doing so, FMA relaxes the assumption of conditional independence within profiles that is characteristic of traditional latent profile analysis (LPA), but is unrealistic for psychological states in daily work life, and can result in spurious latent profiles (Bauer & Curran, 2003; Morin & Marsh, 2015).

[1] We also assessed the FQ in the baseline questionnaire to examine how participants estimated the prevalence of flow states during their work. Specifically, we asked participants how often they experienced flow at work as described by the quotes (i.e., never, less than once a month, at least once a month, at least once every week, at least once every day). Most participants indicated experiencing flow in their job at least once every week (34%), or at least once a month (30%). A minority of employees indicated experiencing flow less than once every month (16%) or at least once every day (15%).

Using FMA,[2] we identified (a) within-person profiles of states that vary across employees to examine their emergence in daily work activities, (b) classes of employees based on the frequency of state profiles to examine their prevalence and differences therein, and (c) predictors of state profiles to examine what predictors differentiate these profiles (Mäkikangas et al., 2018). We tested various FMA models with different constraints to determine which model best suited the data. As recommended in the literature, we began with testing unconstrained models and gradually added constraints whenever convergence or identification issues arose (Asparouhov & Muthén, 2008; Henry & Muthén, 2010). Specifically, we first ran a model with freely estimated means and variances within the latent profiles, and free factor variances while restricting the first factor loading to 1 (Lubke & Luningham, 2017). We set the factor mean of the latent continuous variable to 0 because we freely estimated factor means in the profiles (Lubke & Muthén, 2007). Due to non-normality and missingness in our data, we used MLR estimation and the FIML estimator to avoid biased estimates and standard errors (Asparouhov & Muthén, 2008).[3] Based on previous recommendations (Mäkikangas et al., 2018; Spurk et al., 2020), we started with 1000 starting values and retained 200 sets for the final optimization stage to overcome local solutions. The solution had to be statistically adequate without errors and convergence issues; otherwise, we increased the number of starting values and retained values. Finally, we used raw scores to interpret the level of flow components for the different state profiles.[4]

Considering the inductive nature of person-centered analyses, we compared a series of solutions with different numbers of profiles and classes based on the following fit statistics: Akaike information criterion (AIC), Bayesian information criterion (BIC), and sample size adjusted Bayesian information criterion (aBIC) (Nylund et al., 2007; Tofighi & Enders, 2008). Despite the absence of formal thresholds or criteria to determine fit, optimal solutions will have lower descriptive fit indices (e.g., AIC, BIC) values and higher entropy. Moreover, we examined other fit indices (i.e., entropy and posterior classification probabilities) to investigate whether the optimal solution was theoretically justified and provided substantive meaning and interpretation of the profiles (Hofmans et al., 2020; Spurk et al., 2020). We also graphically presented the different solutions and inspected gradual changes in fit statistics using an elbow plot (Masyn, 2013). After we found the optimal solution, we tested the effects of challenge and hindrance appraisal using the 3STEP procedure in Mplus (Asparouhov & Muthén, 2014). We person-mean centered the challenge and hindrance appraisal scores, essentially focusing on how within-person fluctuations of those challenge and hindrance appraisals related to distinct profiles on the flow components (Enders & Tofighi, 2007).

The supplementary tables and figures (Appendix A), study description and guidelines (Appendix B), measures for this study (Appendix C), annotated syntax and analysis code (Appendix D), and raw data are available at https://osf.io/dwufp/.

4. Results

4.1. Descriptive results

Table 1 shows the descriptive statistics of the study variables. We reported both the separate flow components and the global flow score of those components to shed light on potential differences in relationships between their predictors. Most variables exhibited substantial within-person variance (60%–70%), supporting our multilevel approach (e.g., Xanthopoulou, 2017). Moreover, the correlations between the three flow components were considerably high at the within-person level (0.66–0.69), thus confirming the choice of factor mixture modeling. Furthermore, we examined the reliabilities of the variables using Multilevel Confirmatory Factor Analysis (MCFA). We found that a measurement model including the three separate flow components and predictors at the state level (appraisals) fits the data well ($\chi^2 = 776.14$, $df = 107$, CFI = 0.98, TLI = 0.97, RMSEA = 0.05, $SRMR_{within} = 0.03$), and fits better than a model with all flow components loading on one global flow factor ($\chi^2 = 3123.99$, $df = 114$, CFI = 0.90, TLI = 0.88, RMSEA = 0.10, SRMRwithin = 0.06). Factor loadings of the Psychological Flow Scale (Norsworthy et al., 2023) observed in this study can be found in Supplementary Table 10.

4.2. Hypothesis 1: profiles of states

To test Hypothesis 1, we ran a series of multilevel factor mixture models to examine the state profiles based on constellations of scores on the core flow components. We first analyzed models with freely estimated means and variances (see Appendix D – Model 1). However, we faced convergence issues after including a fifth profile in the one-class solution and a third profile in the two-class solution.

Henceforth, we estimated a more parsimonious model with constrained variances. Similarly, we faced identification issues while

[2] We also conducted multilevel latent profile analyses to examine whether the results were similar, which was indeed the case (see Supplementary Table 7).

[3] We checked the data for deviant observations. Using Mahalanobis distance and corresponding p-values with a cut-off of 0.001, the preliminary analyses revealed the presence of 99 deviant cases (3.38%). However, these observations could potentially originate from a subpopulation in the data, so we did not exclude them from the analyses (Mäkikangas et al., 2018). In addition, we checked the normality of the input variables. Kolmogorov-Smirnov (D (2927) = [0.04–0.20], $p < .001$) and Shapiro-Wilk tests (W (2927) = [0.85–0.99], $p < .001$) showed that the indicator variables do not follow a normal distribution. As such, we employed an MLR estimator with robust standard errors. We did, however, examine whether the solution changed after excluding deviant cases and non-compliant participants, which was not the case (see Supplementary Table 8).

[4] We replicated our findings using grand-mean centered components (see Supplementary Fig. 7). Within-person centering of the flow components is not recommended, as it alters the interpretation of profiles and eliminates between-person variation (Mäkikangas et al., 2018).

Table 1
Means, standard deviations, ICCs, and correlations of study variables.

Variable	*M*	*SD*	ICC	1	2	3	4	5	6	7	8	9
1. Global flow score	4.81	1.19	0.39**	**(0.92)**	0.89*	0.87*	0.89*	0.56*	0.52*	−0.42*		
2. Absorption	5.09	1.34	0.36**	0.93*	**(0.90)**	0.67*	0.69*	0.52*	0.48*	−0.34*		
3. Effortless control	4.93	1.22	0.35**	0.90*	0.78*	**(0.83)**	0.66*	0.51*	0.32*	−0.33*		
4. Intrinsic reward	4.41	1.41	0.40**	0.92*	0.79*	0.73*	**(0.88)**	0.46*	0.56*	−0.44*		
5. Flow Questionnaire[a]	0.37	0.48	0.23**	0.58*	0.52*	0.54*	0.53*	–	0.30*	−0.21*		
6. Challenge appraisal	3.33	0.86	0.32**	0.64*	0.58*	0.46*	0.71*	0.43*	**(0.77)**	−0.43*		
7. Hindrance appraisal	1.80	0.82	0.44**	−0.33*	−0.30*	−0.31*	−0.30*	−0.20*	−0.22*	**(0.81)**		

Note. M = mean. SD = standard deviation. ICC = intraclass correlation coefficient.
Means and standard deviations were reported on a 7-point (i.e., flow components) and 5-point (i.e., appraisals) Likert scale.
The global flow score is computed based on the average of the three core flow components.
Correlations above the diagonal represent state-level correlations involving within-person-centered variables (n = 2927). Correlations below the diagonal represent employee-level correlations with grand-mean centered variables (N = 199) and state-level variables aggregated to the employee level.
Average reliability is reported in **bold** along the diagonal for state-level (Omega within) and employee-level (Omega between) measures.
[a] 0 = no, 1 = yes.
* $p < .01$.
** $p < .001$.

freely estimating factor variances and thus estimated a more constrained model with freely estimated factor loadings and fixed factor variances (see Appendix D – Model 2).[5]

Table 2 shows the fit indices for FMA models with two to eight profiles (at the state level) and one to four classes (at the employee level). We primarily examined solutions with three to four classes at the employee level, because the fit indices were considerably better than for solutions with one or two classes. Solutions with five classes (and more) did not converge. To facilitate the interpretation of these profiles, we present elbow plots in the appendix (see Supplementary Figs. 1–4). Regarding the within-person profiles at the state level, we mainly considered the six-profile solution because it fitted best with the data and was theoretically the most interesting. Both in the solutions with three and four classes at the employee level (which showed the best overall fit indices), the improvement in model fit began to diminish when going beyond six profiles at the state level. Specifically, the decrease in the aBIC value was substantially smaller when moving from six to seven state-level profiles (a decrease of 97) compared to the decrease (182) when going from five to six state-level profiles. These results offer a first indication that a six-profile state-level solution may be a good fit for the data and that the optimal solution could be somewhere between five and seven state-level profiles.

When adding a sixth state-level profile, an additional profile emerged that differed in shape (i.e., high levels of effortless control only, which we labelled as boredom), thus providing an interesting contribution as a unique constellation beyond level differences on all three flow components. Theoretically, this profile enriched the five-profile state-level solution because it aligned with the 'boredom' state from the EFM (i.e., employees feeling unfocused and unfulfilled, although highly in control) (Massimini et al., 1987) (see Fig. 1). Statistically, the average latent class probability for individuals assigned to Profile 6 was 0.82, while the classification probability was 0.81, both indicating that most members are likely to truly belong to this profile (Spurk et al., 2020).

Including a seventh profile resulted in an additional state-level profile with high levels of absorption and intrinsic reward, yet moderate effortless control, potentially referring to a state of ecstasy or euphoria (e.g., during skydiving). This profile, however, did not match any of the eight state profiles described in the experience fluctuation model. Thus, although interesting, its theoretical grounding is limited. Statistically, both the elbow plots (Supplementary Fig. 3) and fit indices (Table 2) suggest that there is little added value in including this profile, given the small gains in fit indices. Additionally, this profile contained only a few observations (i.e., n = 79, 3%), making it too small to be substantively interpretable (Lubke & Neale, 2006). Finally, this profile showed lower classification accuracy (i.e., 0.80) and classification probability (i.e., 0.68) with notable cross-classification probabilities, indicating that individuals assigned to this profile have a substantial chance of belonging to neighbouring profiles (Woo et al., 2018).

All in all, these findings suggest that state-level profile seven is less clearly defined and may jeopardize the conceptual distinctiveness of the other state profiles. Importantly, these findings were replicated among two subpopulations using a random split in our sample (see Supplementary Table 11), showing that the sixth state-level profile was relatively robust. Therefore, we feel confident in the six-profile solution, offering an interesting contribution to the five-profile solution while being more substantiated (theoretically and statistically) than the seven-profile solution.

Regarding the number of classes (at the employee level) with this six-profile solution (at the state level), a fourth class provided little additional theoretical insights compared to the three-class solution. More specifically, the differences between classes three and

[5] To further interpret our final solution, we ran a model with unconstrained factor variances for the profile that theoretically aligned most closely with the deep flow concept, which allowed us to examine the continuous nature of flow (i.e., the amount of within-profile variation in flow scores) (see Appendix D – Model 3). A model with freely estimated factor variances within the Deep Flow profile (see below) (e.g., log-likelihood = −11,484.75, aBIC = 23,171.28) slightly outperformed a model with constrained factor variances for this profile (e.g., log-likelihood = −11,504.68, aBIC = 23,206.33). The significant within-profile variance of the latent flow factor (variance = 0.44, $p < .001$) indicates that, although members of this profile generally reported similar scores on the flow components, substantive individual variation remained.

Table 2
Fit indices and profile membership for within-person state profiles (H1).

#Classes	#Profiles	Log-likelihood (parameters)	Profiles (%)	Classes (%)	AIC	BIC	aBIC	Entr	aBIC difference
1	2	−12,376.16 (13)	0.92/08	–	24,778.32	24,856.08	24,814.78	0.88	–
1	3	−12,268.99 (17)	0.05/0.90/0.04	–	24,571.98	24,673.67	24,619.66	0.89	−195.12
1	4	−12,156.49 (21)	0.77/0.04/0.13/0.05	–	24,354.97	24,480.59	24,413.87	0.81	−205.79
1	5	−12,073.75 (25)	0.03/0.77/0.14/0.03/ 0.04	–	24,197.50	24,347.04	24,267.61	0.83	−146.26
1	6	−12,023.41 (29)	0.04/0.13/0.04/0.02/ 74/0.02	–	24,104.82	24,278.29	24,186.14	0.83	−81.47
1	7	−11,988.64 (33)	0.04/0.73/0.02/0.02/ 0.04/0.02/0.12	–	24,043.29	24,240.68	24,135.83	0.82	−50.31
1	8	−11,957.93 (37)	0.00/0.08/0.10/0.05/ 0.04/0.01/0.70/0.08	–	23,989.86	24,211.19	24,093.62	0.82	−42.21
2	2	−12,137.95 (15)	0.53/0.47	0.53/0.47	24,305.90	24,395.62	24,347.96	0.80	–
2	3	−11,993.59 (20)	0.47/0.14/0.39	0.43/0.57	24,027.18	24,146.82	24,083.27	0.79	−264.69
2	4	−11,878.28 (25)	0.02/0.40/0.42/0.15	0.43/0.57	23,806.57	23,956.11	23,876.68	0.84	−206.59
2	5	−11,755.21 (30)	0.46/0.33/0.05/0.05/ 0.11	0.63/0.37	23,570.42	23,749.88	23,654.55	0.85	−222.12
2	6	−11,679.38 (35)	0.33/0.45/0.03/0.03/ 0.03/0.11	0.63/0.37	23,428.76	23,638.12	23,526.91	0.84	−127.64
2	7	−11,625.26 (40)	0.32/0.44/0.04/0.11/ 0.03/0.03/0.02	0.64/0.36	23,330.52	23,569.79	23,442.69	0.85	−84.22
2	8	−11,576.93 (45)	0.03/0.32/0.44/0.09/ 0.03/0.04/0.02/0.03	0.63/0.37	23,243.87	23,513.05	23,370.06	0.86	−72.63
3	2	−12,090.12 (17)	0.72/0.28	0.38/0.52/0.09	24,214.24	24,315.93	24,261.92	0.84	–
3	3	−11,854.42 (23)	0.09/0.37/0.54	0.45/0.45/0.10	23,754.86	23,892.44	23,819.36	0.85	−442.56
3	4	−11,722.75 (29)	0.50/0.09/0.04/0.37	0.13/0.47/0.40	23,503.51	23,676.98	23,584.83	0.89	−234.52
3	5	−11,609.67 (35)	0.03/0.07/0.45/0.13/ 0.32	0.35/0.37/0.29	23,289.37	23,498.73	23,387.52	0.88	−197.31
3	**6**	**−11,504.68 (41)**	**0.05/0.13/0.44/ 0.29/0.05/0.05**	**0.37/0.32/ 0.31**	**23,091.35**	**23,336.61**	**23,206.33**	**0.88**	**−181.19**
3	7	−11,441.60 (47)	0.45/0.05/0.12/0.28/ 0.03/0.04/0.03	0.31/0.32/0.37	22,977.20	23,258.34	23,109.00	0.88	−97.33
3	8	−11,391.25 (53)	0.30/0.03/0.44/0.09/ 0.03/0.05/0.04/0.02	35/0.15/0.50	22,888.51	23,205.54	23,037.14	0.87	−71.86
4	2	−12,084.93 (19)	0.74/0.27	0.08/0.48/ 0.29/0.15	24,207.85	24,321.50	24,261.13	0.77	–
4	3	−11,824.59 (26)	0.40/0.09/0.51	0.27/0.11/ 0.23/0.39	23,701.17	23,856.70	23,774.08	0.82	−487.05
4	4	−11,633.29 (33)	0.46/0.08/0.33/0.13	0.32/0.35/ 0.24/0.10	23,332.57	23,529.97	23,425.11	0.88	−348.97
4	5	−11,501.87 (40)	0.13/0.42/0.05/0.33/ 0.07	0.13/0.33/ 0.21/0.33	23,083.74	23,323.01	23,195.92	0.88	−229.19
4	6	−11,388.44 (47)	0.13/0.06/0.29/0.43/ 0.03/0.05	0.32/0.36/ 0.20/0.13	22,870.87	23,152.02	23,002.68	0.89	−193.24
4	7	−11,326.09 (54)	0.06/0.03/0.03/0.13/ 0.40/0.05/0.31	0.15/0.34/ 0.20/0.31	22,760.18	23,083.19	22,911.61	0.89	−91.07
4	8	−11,277.09 (61)	0.06/0.32/0.03/0.02/ 0.04/0.40/0.03/0.11	0.34/0.20/ 0.32/0.13	22,676.19	23,041.07	22,847.25	0.89	−64.36
5	2	−12,084.23 (21)	0.27/0.73	0.46/0.09/ 0.04/0.12/0.29	24,210.45	24,336.07	24,269.35	0.72	–
5	3	−11,800.83 (29)	0.40/0.08/0.52	0.26/0.04/ 0.38/0.23/0.09	23,659.66	23,833.13	23,740.99	0.83	−528.36
5	4	–	–	–	–	–	–	–	–

Note. AIC = Akaike Information Criterion (AIC). BIC = Bayesian Information Criterion. aBIC = sample-adjusted BIC. Entr = entropy. Difference in aBIC = difference in sample-adjusted BIC between previous profile solution.
The final solution is provided in **bold**.

four were somewhat ambiguous, as employees reported experiencing the same profiles (i.e., Microflow, Apathy, and Boredom) to a roughly similar extent. As such, we decided that a three-class solution with six state-level profiles was most appropriate.

Although we only collected data in one sample, we randomly split all participants into two subgroups to test the generalizability of our final solution ($N_1 = 101$, $n_1 = 1444$; $N_2 = 98$, $n_2 = 1483$). We first retained our six-profile state-level solution for both subgroups because the BIC and aBIC consistently decreased when adding new state-level profiles. However, the added value decreased after the sixth state-level profile (See Supplementary Table 11 and Supplementary Figs. 5–6). To examine whether the latent state-level profiles differed across both subgroups, we followed the approach of Morin et al. (2016) and tested a series of increasingly constrained models reflecting structural, dispersion, and distributional similarity. Although each successive model imposed additional constraints (i.e., equality of means, variances, and profile proportions), the BIC and aBIC consistently decreased (see Supplementary Table 12). These

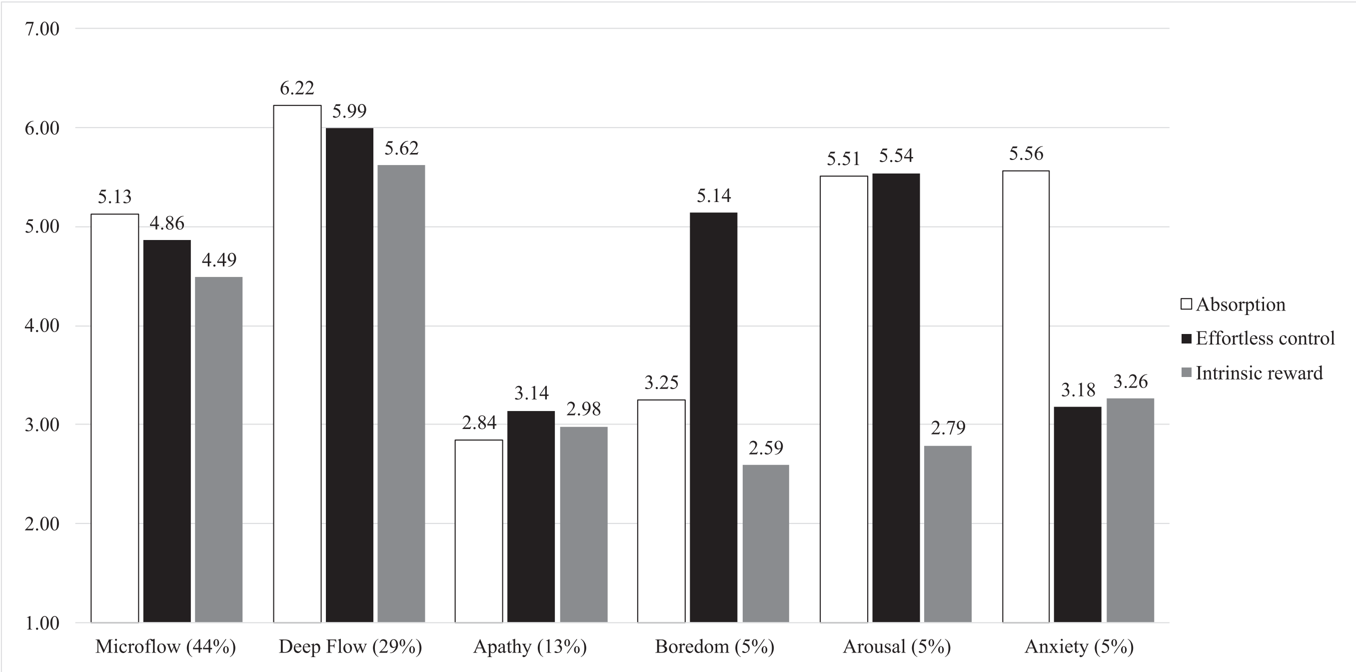

Fig. 1. Overview of the final within-person state profiles at work (H1).
Note. Final six-profile solution of the Multilevel Factor Mixture Analyses, based on means of the three flow components (absorption, effortless control, and intrinsic reward) across profiles. Flow components are raw scores on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). Three profiles emerged that differ in level (Microflow, Deep Flow, and Apathy) and three that differ in shape (Boredom, Arousal, and Anxiety).

findings suggest that the presence, structure, and characteristics of the six state-level profiles are likely invariant across groups, supporting their generalizability.

Table 3 and Fig. 1 present the within-person profile estimates of our final six-profile state-level solution. We labelled these profiles based on the Experience Fluctuation Model (e.g., Massimini et al., 1987) to theoretically ground them in existing flow literature (e.g., Inkinen et al., 2014; Lambert et al., 2013). As expected, three profiles emerged, differing primarily in terms of the level of each of the three components. We labelled the profile with the highest levels as "Deep Flow" ($n = 851$, 29%), as this state is characterized by peak levels of absorption ($M = 6.22$), effortless control ($M = 5.99$), and reward ($M = 5.62$). The second profile ($n = 1289$, 44%) was characterized by relatively high levels of absorption ($M = 5.13$), effortless control ($M = 4.86$), and reward ($M = 4.49$). We labelled this state as "Microflow" because employees feel a certain degree of focus, fulfillment, and control, although not at the level of Deep Flow (Clarke & Haworth, 1994). The third profile ($n = 371$, 13%) is characterized by a low level of absorption ($M = 2.84$), effortless control ($M = 3.14$), and reward ($M = 2.98$). We referred to this profile as "Apathy" given the low levels on all components, suggesting that employees feel rather disengaged and indifferent to perform their activity (Delle Fave & Massimini, 2005).

Furthermore, three profiles emerged that had different constellations of scores on the three flow components. We labelled the fourth profile ($n = 142$, 5%), characterized by low levels of absorption (3.25) and reward (2.59), yet high levels of effortless control (5.14), as "Boredom". Aligned with the EFM, this state refers to a situation with little challenge and minimal use of skills, making employees unfocused, passive, and unfulfilled (Massimini & Carli, 1988). The fifth profile ($n = 135$, 5%) is characterized by high levels of absorption ($M = 5.07$) and effortless control ($M = 5.54$), but low reward ($M = 2.79$). We labelled this state as "Arousal" because, despite feeling activated (as reflected by high levels of absorption and effortless control), employees in this state risk also feeling tense and stirred up (as reflected by the low levels of intrinsic reward) (Inkinen et al., 2014). Finally, we labelled the sixth profile ($n = 139$, 5%) as "Anxiety" because employees feel highly absorbed ($M = 5.56$) but score low on effortless control ($M = 3.18$) and intrinsic reward ($M = 3.26$). Anxiety reflects a state where challenges are high and skills low, resulting in doubts regarding one's ability to cope with highly challenging activities and worries about potential negative outcomes (Massimini et al., 1987). Accordingly, unlike the Arousal profile, low levels of effortless control (see Fig. 1) reflect feelings of distress, tension, and concerns that employees report during this state, whereas those aroused typically still feel in control (Massimini & Carli, 1988). Note that we decided not to label this state profile as "worry" (another profile in the EFM experience model), because previous empirical research has shown that the worry profile occurs infrequently and conceptually overlaps with anxiety (Clarke & Haworth, 1994; Haworth & Evans, 1995). This overlap raises concerns about concept redundancy and points toward the presence of a spurious profile. In addition, we would have expected a typical "worry" profile to emerge at low levels of intrinsic reward and effortless control, but moderate levels of absorption, since employees likely lack the cognitive capacity to fully focus on their activity due to ongoing rumination. On the other hand, anxiety is an established state characterized by high rather than moderate absorption (Massimini et al., 1987) and is typically described in terms of worry. Therefore, we opted for this broader, theory-consistent label (Weidman et al., 2017).

We also tested to what extent these profiles overlap with discrete flow states as measured by the Flow Questionnaire. 46% of states labelled as flow according to the FQ corresponded to those in the Deep Flow profile, while another 44% corresponded to the Microflow profile.[6] The overlap with the other profiles was negligible. Because previous research has demonstrated that the FQ is well equipped to detect both Microflow and Deep Flow states[7] (Moneta, 2021), these findings support the concurrent validity of the two flow profiles (i.e., Deep Flow and Microflow) while also supporting the discriminant validity of the other state profiles.

Thus, in support of Hypothesis 1, our results show that daily psychological states during work are characterized by quantitatively (i.e., Apathy, Microflow, and Deep Flow) and qualitatively (Arousal, Anxiety, and Boredom) different constellations of the flow components. Two flow profiles were found: one with peak scores on absorption, effortless control, and intrinsic reward (i.e., Deep Flow), and one with moderately high scores on the three components (i.e., Microflow).

4.3. Hypothesis 2: the prevalence of flow

To examine the frequency of flow states during daily work activities, we examined the prevalence of the different profiles in the selected FMA solution. We found that participants experienced Deep Flow during 29% of their work activities, whereas Microflow was experienced in 44% of the work activities. (see Table 3). In support of Hypothesis 2, these findings suggest that Deep Flow is a relatively infrequent state, occurring in approximately one out of every three work activities and only for brief moments (see Supplementary Table 5), whereas Microflow is more commonly observed in daily work life.

4.4. Hypothesis 3: individual differences in the prevalence of (flow) states at work

To test Hypothesis 3, we first examined whether the prevalence of the Deep Flow and Microflow state profiles varied significantly across employees, following the approach of Mäkikangas et al. (2018) (see Appendix D – Model 4). To do so, we tested a model with a random effect for both profiles at Level 2, while fixing the profile structure at Level 1. The significant variance estimates within the

[6] When participants reported experiencing flow (as measured by the FQ), it most often occurred only once during an activity (58%) and was relatively brief, typically lasting less than 10 min (30%) or between 10 and 30 min (45%) (see Supplementary Table 5).

[7] We used a shorter version of the FQ developed by Delle Fave et al. (2011) to reduce participant burden, which, according to Moneta (2021), primarily captures microflow states. The full version of the FQ that also includes deep flow quotes (see Moneta, 2021) may have been better at capturing deep flow states.

Table 3
Descriptive information of the within-person state profiles (H1–H2).

Profile	%	FQ %	Absorption		Effortless control		Intrinsic reward	
			M	Var	*M*	Var	*M*	Var
"Microflow"	44%	44%	5.13	0.67	4.86	0.61	4.49	0.93
"Deep Flow"	29%	46%	6.22	0.55	5.99	0.56	5.62	0.88
"Apathy"	13%	1%	2.84	0.54	3.14	0.78	2.98	1.14
"Boredom"	5%	1%	3.25	0.73	5.14	0.75	2.59	1.34
"Arousal"	5%	5%	5.51	0.70	5.54	0.72	2.79	0.89
"Anxiety"	5%	2%	5.56	0.68	3.18	0.54	3.26	1.84

Note. M = mean. Var = variance.
FQ % = Percentage of 'yes' responses to the FQ that correspond to the state profile.

Deep Flow (11.09, SE = 2.85, $p < .001$) and Microflow (7.62, SE = 1.87, $p < .001$) profiles indicate that employees differed meaningfully in how frequently they reported both states.

To examine individual differences in the prevalence of the different profiles, we then interpreted the employee-level classes as identified in the optimal multilevel FMA solution (see Table 4). The results first demonstrate the presence of a class of employees (N = 62, 31%) who predominantly experience Deep Flow (i.e., during 86% of the work activities, those employees selected and reported on).[8] We labelled this class as "Deep Flow-ers", as originally conceptualized by Csikszentmihalyi (2000).

The second class describes employees (N = 74, 37%) who predominantly experience Microflow (92%), while rarely experiencing Deep Flow (1%). We labelled this class as "Microflow-ers", reflecting employees who are typically absorbed, experience effortless control, and feel intrinsically rewarded to some extent, but rarely reach the intensity of Deep Flow. The third and final latent class represents 32% of the employees (N = 63), and they either experience Apathy (32%), Microflow (31%), or Boredom (15%), but rarely Deep Flow (6%). We labelled this class as "Ambivalent" because these employees obtain both positive (i.e., Microflow) and negative (i.e., Apathy) states at work (e.g., Rothman et al., 2017).

In answering Hypothesis 3, we found that our sample could be divided into three distinct groups: a relatively small group of employees who frequently experience the Deep Flow profile (31%), a larger group of employees who rarely experience Deep Flow but mostly experience Microflow (37%), and a third group that experiences Microflow or Apathy (32%). These employee-level results further substantiate how deep flow is an infrequent state for most employees, as 69% rarely experience it. When microflow is also taken into account, however, flow states are much more common.

4.5. *Hypotheses 4a–4c: predictors of states*

To test Hypotheses 4a-c, we further explored whether challenging and hindering appraisals of activities were related to state profiles based on constellations of scores on the flow components (see Appendix D – Model 5). Our results largely supported our expectations (see Table 5). More specifically, results of the multinomial regression analysis with Deep Flow as reference category showed that, at the within-person level, employees who appraised their activity as challenging were less likely to experience Arousal ($OR = 0.02, p < .001$), Apathy ($OR = 0.02, p < .001$), Microflow ($OR = 0.07, p < .001$), Boredom ($OR = 0.01, p < .001$), or Anxiety ($OR = 0.05$, $p < .001$). In contrast, employees who appraised their activities as hindering were more likely to experience Arousal (OR = 4.84, $p < .05$), Apathy ($OR = 7.16, p < .001$), Microflow ($OR = 2.73, p < .01$), Boredom ($OR = 6.09, p < .001$), or Anxiety ($OR = 9.86, p < .001$) compared to experiencing Deep Flow. We did not find that the interaction between challenge and hindrance appraisal predicted membership in any of the profiles, suggesting that they separately contribute to the emergence of Deep Flow states.

To facilitate the interpretation of these findings, we visualized the mean levels of challenge and hindrance appraisals across the six state profiles in Fig. 2. As expected, the predictors of the three profiles that differed in level (i.e., Apathy, Microflow, and Deep Flow) depicted a positive trend for challenge appraisal and a negative trend for hindrance appraisal, with the highest (lowest) levels of challenge (hindrance) appraisal associated with the Deep Flow profile and the second-highest (lowest) levels of challenge (hindrance) appraisal associated with Microflow. Interestingly, compared to Arousal, Anxiety was characterized by higher challenge appraisals accompanied by relatively high hindrance appraisals, suggesting that employees perceive the situation as not only demanding but also constraining or overwhelming (Massimini & Carli, 1988). In support of Hypotheses 4a–b, and not 4c, these linear patterns align with flow theory, indicating that when activities are perceived as challenging, relevant for future growth, and not as hindering, (deep) flow is more likely to emerge than other states (Csikszentmihalyi & LeFevre, 1989).

[8] To ensure that the observed prevalence was not driven by response patterns, we plotted our final solution using grand-mean centering (see also Mäkikangas et al., 2018). The resulting six state-level profiles showed similar shapes, levels, prevalence, and interpretation (see Supplementary Fig. 7). Moreover, the prevalence of the classes remained consistent even after excluding extreme observations, careless responses, and non-compliant participants (see Supplementary Tables 8 and 9), suggesting that our solution is robust to these potential biases. The prevalence and meaning of the employee-level classes remained consistent, addressing concerns raised in previous Experience Fluctuation Model studies regarding response patterns and raw scores versus centering (see also Ellis et al., 1994). It is important to note, however, that employees in this class did not experience deep flow during 86% of their working time, but rather during 86% of their work-related activities, with individual deep flow states often lasting less than 30 min (see Supplementary Table 5).

Table 4
Descriptive information for the employee-level classes (H3).

Profile	% State profile prevalence within class (*n* states)		
	C1 "Deep Flow-ers" ($N = 62$)	C2 "Microflow-ers" ($N = 74$)	C3 "Ambivalent" ($N = 63$)
"Microflow"	0% ($n = 1$)	**92% ($n = 1005$)**	**31% ($n = 283$)**
"Deep Flow"	**86% ($n = 792$)**	1% ($n = 7$)	6% ($n = 52$)
"Apathy"	4% ($n = 35$)	4% ($n = 48$)	**32% ($n = 288$)**
"Boredom"	1% ($n = 6$)	0% ($n = 0$)	**15% ($n = 136$)**
"Arousal"	4% ($n = 35$)	0% ($n = 2$)	11% ($n = 98$)
"Anxiety"	6% ($n = 56$)	3% ($n = 31$)	6% ($n = 52$)

Note. C1 = Class 1. C2 = Class 2. C3 = Class 3. The most prevalent state profiles for each class are shown in **bold**.

5. Discussion

This study clarifies the nature of flow by empirically demonstrating its distinctiveness from other psychological states, thereby helping to resolve longstanding ambiguities surrounding its uniqueness and conceptual boundaries (Fullagar et al., 2017; Fullagar & Kelloway, 2013). Using data from a day reconstruction study among 199 employees, we demonstrate how constellations of the three flow components represent six phenomenologically distinct state profiles that do not all theoretically align with the flow concept (H1). The profile with peak levels on all three components occurs relatively infrequently (H2) for most employees (H3) and depends on appraising work activities as challenging or not as hindering (H4a–b). As such, this study offers significant contributions to conceptual, theoretical, and methodological advancements in the flow literature, with important implications for future research on the concept of flow and for vocational research more broadly.

5.1. Conceptual contributions

This study situates itself within a broader movement in vocational research toward a more fine-grained understanding of the psychological states that unfold during daily work life by advancing knowledge on the conceptual distinction between flow and non-flow states. Because the three flow components are important indicators of sustainable careers (e.g., De Vos et al., 2020; Nash, 2024) and predictors of employees' health and performance (e.g., Aust et al., 2022; Liu et al., 2023), it is important to understand when and how they take shape during daily work activities. We found that there appears to be a state profile that most closely resembles the conceptual definition of deep flow and is conceptually distinct from non-flow states, as all three components are experienced at a peak level in this state profile (Csikszentmihalyi, 2000; Norsworthy et al., 2021). As such, this study advances conceptual clarity by demonstrating that deep flow is empirically distinguishable from other constellations of the flow components, calling for a reconceptualization of deep flow that better reflects its peak, discrete nature.

A second contribution is that we advance knowledge on the continuous nature of flow. Specifically, we not only found that the variance within the deep flow profile was significant, but also that another profile exists that theoretically aligns with the microflow concept (Csikszentmihalyi, 2000). This state is conceptually distinct from deep flow in the sense that the constellation of the flow components is similar, yet at a lower level. Indeed, our findings suggest that employees can experience a moderate state of absorption, effortless control, and intrinsic reward, but at a lower intensity than deep flow, aligning with the idea of microflow (Csikszentmihalyi, 2000). This finding adds nuance to existing conceptual debates (cf. Abuhamdeh, 2020; Peifer & Engeser, 2021) by showing that flow is neither entirely continuous nor strictly discrete, and advances knowledge on the nature of psychological states within vocational research in general (Hofmans et al., 2020). In doing so, this study responds to a growing recognition within vocational research that understanding when and why daily psychological states emerge requires moving beyond continuous operationalizations toward approaches that capture their quantitative and qualitative differences (Spurk et al., 2020).

5.2. Theoretical contributions

This study contributes to the growing effort in vocational research to map the range of psychological states that shape how employees engage with their daily work activities. Our findings highlight the importance of distinguishing among psychological states within theoretical frameworks based on both the level and the constellation of their underlying components. Without such differentiation, theoretical models risk conflating distinct states, thereby obscuring meaningful variation in employees' experiences. Specifically, our findings add to previous state taxonomies (e.g., Massimini et al., 1987) by demonstrating that employees' daily states during work are characterized by unique combinations of absorption, effortless control, and intrinsic reward. Instead of a priori classifying states into distinct profiles based on challenge and skill ratios – like the EFM – our person-centered approach inductively derived these state profiles (Hofmans et al., 2020). By doing so, we complement prior taxonomies by avoiding profiles that represented a limited range of states and may not fit the data.

For instance, in several previous EFM studies, the worry profile was identified (e.g., Massimini et al., 1987). However, we did not find strong support for its presence, likely due to its conceptual overlap with anxiety (Haworth & Evans, 1995). In addition, the microflow profile we found conceptually aligned with the control profile from the EFM (Clarke & Haworth, 1994), a state lacking empirical investigation (e.g., Weidman et al., 2017). Microflow and control both reflect states in which skills are sufficient relative to

Table 5
Results of the within-person predictors (H4a–c).

Variable	Arousal vs Deep Flow			Apathy vs Deep Flow			Microflow vs Deep Flow			Boredom vs Deep Flow			Anxiety vs Deep Flow		
	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*	Coef.	*SE*	*OR*
Challenge appraisal	−3.73***	0.91	0.02	−4.11***	0.63	0.02	−2.61***	0.37	0.07	−4.99***	0.74	0.01	−2.97***	0.66	0.05
Hindrance appraisal	1.58*	0.63	4.84	1.97***	0.46	7.16	1.00**	0.36	2.73	1.81***	0.52	6.09	2.29***	0.52	9.86
Challenge × hindrance appraisal	−0.04	0.63	0.96	−0.03	0.58	0.97	0.12	0.54	1.13	−0.03	0.57	0.97	−0.42	0.64	0.66

Note. Coef = unstandardized coefficients. *SE* = standard error. *OR* = odds ratio.
Deep Flow is the comparison profile. Negative coefficients indicate that higher values of the predictors reduce the chance of experiencing another profile (e.g., Arousal) versus experiencing the comparison profile (i.e., Deep Flow), and vice versa for positive coefficients.
Odds ratios above 1 indicate that another profile (e.g., Arousal) is more likely to occur for higher values of the predictors than the comparison profile (i.e., Deep Flow), and vice versa for odds ratios below 1.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

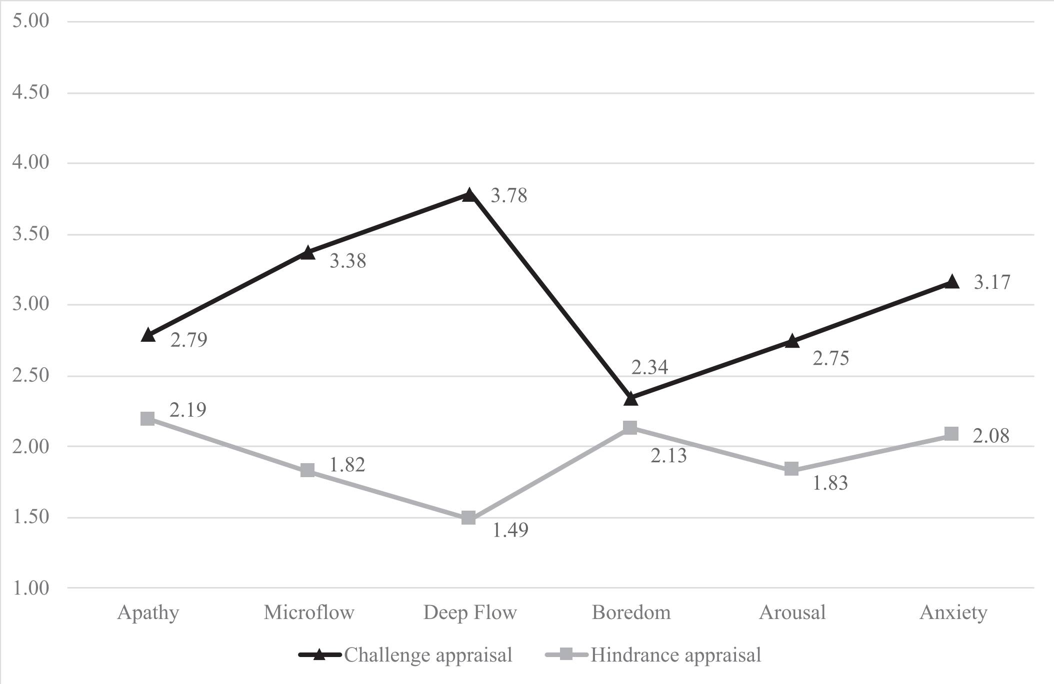

Fig. 2. Challenge and hindrance appraisal levels across the state profiles (H4a–c).

the challenges, fostering a sense of competence and manageability, yet without the heightened level of intensity that characterizes deep flow (Haworth & Evans, 1995). Moreover, the only difference between microflow and control is a small change in how challenging the activity feels. Since challenge and skill are closely linked and hard to separate (Norsworthy et al., 2021), and our findings showed a linear pattern of challenge appraisal differentiating between microflow and deep flow, the conceptual difference between control and microflow may be ambiguous. Therefore, following Csikszentmihalyi (2000), we chose the label 'Microflow'.

The present study also contributes to our understanding of the predictors that distinguish flow from non-flow states by demonstrating how the appraisal of work activities as challenging or hindering is associated with distinct psychological states (Peifer & Tan, 2021). Specifically, we extend the Challenge Hindrance Stressors Framework (CHSF) by demonstrating how appraisals of work activities relate not only to the occurrence of flow but also to a broader range of psychological states during work (LePine, 2022). In doing so, we respond to calls from scholars to investigate how appraisals play a critical role in shaping employees' daily states (LePine, 2022; O'Brien & Beehr, 2019). Additionally, we complement previous research studying relationships between flow and stressors at the day, person, or team level (e.g., Feng, 2022; Feng et al., 2024; van Oortmerssen et al., 2020) by studying associations in flow and its predictors at the activity level, thereby offering a deeper understanding of its actual occurrence during work and how employees experience their daily activities.

Finally, the present study also enhances our understanding of the prevalence of flow states among employees. Specifically, we challenge the assumption that flow emerges to some extent during all activities and for all employees and underscore the importance of tailoring theoretical models to account for such individual differences. Regarding these differences, we found evidence for an employee group exhibiting a higher likelihood of experiencing deep flow (Tse et al., 2020; Ullén et al., 2012) and two other groups with a low likelihood of experiencing deep flow. These findings may provide relevant insights for career development because, unlike the assumption that all activities to some extent vary in flow intensity, they rather highlight that deep flow states are not the default state during work activities for many employees. Because employees with few deep flow states may also have fewer opportunities to strengthen their skills, feel mastery, and develop motivation (Liu et al., 2023), such individual differences might pose a brake on the level of sustainable career that can be achieved for some employees (De Vos et al., 2020). Accordingly, examining how often employees experience deep flow and other states can further help scholars explain differences in vocational outcomes and predict long-term career growth and health (e.g., Van der Heijden & Bakker, 2011).

5.3. *Methodological contributions*

By collecting data via the day reconstruction method (DRM), this study also addresses calls to understand its effectiveness for the study of flow (Moneta, 2021; Xanthopoulou, 2017). When studying flow as a peak discrete state, less intrusive, less intense, or event-based protocols are required (Scollon et al., 2003; Shiffman et al., 2008) because traditional ESM studies relying on (semi-)random assessments risk interfering with or missing out on flow states (Bartholomeyczik et al., 2024; Hektner et al., 2007). This approach paves the way for research avenues into the effectiveness and respective merits of ESM and DRM in studying flow. By examining constellations of scores on the flow components and illustrating that not all states vary on the flow continuum, we also extend previous research predominantly using global flow scores or arbitrary thresholds to distinguish deep flow from other states (Delle Fave & Bassi, 2023). Our findings thus suggest that reducing flow to a global score or assessing flow with only one or two components oversimplifies its complexity, neglecting the distinct psychological states that exist across the three core flow components.

In addition, using a person-centered approach (Mäkikangas et al., 2018) allowed us to offer insights into the actual prevalence of unique constellations of scores on the three flow components, instead of imposing state profiles in the data. We also extend previous person-centered research on flow by applying a multilevel approach and identifying both within-person state profiles and employee-level classes (e.g., Kawabata & Evans, 2016; Mäkikangas et al., 2010; Rouxel et al., 2023). Accordingly, we address recent calls to integrate person-centered techniques with multilevel and longitudinal designs to capture within-person profiles (Hofmans et al., 2020; Woo et al., 2024), a direction that has remained largely unexplored in the flow literature. Moreover, we complement prior person-centered approaches by using factor mixture modeling, thereby capturing constellations differing in shape and level (Meyer & Morin, 2016), rather than only level differences (e.g., Kawabata & Evans, 2016). These newly implemented techniques can help scholars overcome the limitations of treating all observations in the data as varying on the flow continuum by simultaneously capturing the discrete as well as the continuous nature of flow.

5.4. Limitations and future research directions

The findings of our study should be understood in light of certain limitations related to our methodological choices. One choice was the use of single-source quantitative data. We were thus unable to address potential common method bias (P. Podsakoff et al., 2024). Additionally, assessing flow at the end of each activity prevented us from capturing potential short-term flow fluctuations within the same work activity (Peifer & Engeser, 2021). Given the rise of wearable technologies and other objective measurement approaches to detect flow (e.g., Gaggioli et al., 2013; Rissler et al., 2023), future research could uncover how employees enter and exit flow states within and between activities by integrating self-reported and physiological or neuroscientific measures of flow.

Another limitation is the lack of work-related flow outcomes and measuring flow-related states to externally validate our findings (Spurk et al., 2020). Whereas research consistently demonstrates that flow is beneficial for employees' (long-term) performance and well-being in their careers (Aust et al., 2022; Liu et al., 2023), we could have included constructs assessing performance or well-being to directly test this notion. This approach would also have allowed us to further substantiate our claims that (deep) flow states are qualitatively distinct from other states. Future research validating our profiles by including relevant work-related outcomes would significantly increase the practical relevance of the findings and support the importance of distinguishing between flow and non-flow states.

Moreover, testing how constellations of the flow components associate with other, yet related, constructs (e.g., engagement, positive affect, happiness) (Navarro et al., 2022) could also have provided insights into conceptual differences between flow and these constructs. Hence, future research could directly measure flow-related states and conduct further discriminant validity tests to accurately distinguish and isolate flow (Fullagar & Kelloway, 2013) or extend our factor mixture approach to explore distinct factors of flow and related states (Kim et al., 2025). These limitations also open the possibility for research with other person-centered analyses (e.g., latent transition analysis, growth mixture modeling) (e.g., Harju et al., 2023; Mäkikangas, 2018) that allow assessing how employees shift between flow and other states during daily work activities.

Another set of limitations relates to the use of a single sample consisting of full-time, white-collar employees predominantly residing in the UK. Consequently, we must acknowledge the potential instability of the profiles and classes across different samples and the limited ability to generalize our findings to other cultures or contexts. We did take several measures to ensure the robustness of the profiles at the activity level (i.e., illustrating no evidence for selection biases, demonstrating the robustness across two random subgroups, gathering a large sample size). Nevertheless, the limited geographical scope of our sample and the use of Prolific may have differentiated our classes at the employee level from other occupations or employee groups. These limitations open up the possibility for future research using field studies to test the presence and prevalence of the state profiles across different occupations (e.g., Csikszentmihalyi & LeFevre, 1989), cultures (e.g., Delle Fave & Massimini, 2005), organizational roles (e.g., Sartori & Delle Fave, 2014), or within unique samples (e.g., mountain climbers, Delle Fave et al., 2003; deer hunters, Everett & Gore, 2015), to examine differences between samples and populations and thereby evaluate the stability of our profiles and classes.

Finally, to minimize participant burden, we only studied flow during work-related activities. Whereas research indicates that the nature of flow does not differ between jobs (e.g., Massimini et al., 1987), the underlying dynamics between flow components might vary between work-related and non-work activities (Csikszentmihalyi & LeFevre, 1989; Delle Fave & Massimini, 2005; Haworth & Hill, 1992). For instance, we did not find a profile that scored high on the intrinsically rewarding component of flow in our sample of work-related activities (which would theoretically align with the state of 'relaxation'; Massimini & Carli, 1988). Because some employees may feel more rewarded when engaging in leisure activities (Bassi & Delle Fave, 2012; Engeser & Baumann, 2016), future studies could, for instance, sample leisure activities and compare the number and prevalence of profiles with work-related activities.

6. Practical recommendations

The finding that microflow and deep flow states are not omnipresent for all employees, but still a meaningful part of daily vocational experience, makes them a highly relevant target for workplace interventions (Liu et al., 2023). As such, our findings have important implications for policies and practices aimed at fostering employees' long-term growth, health, and employability while building a sustainable career (Dik et al., 2015; Nash, 2024; Van der Heijden & Bakker, 2011). What policies, interventions, and practices can organizations, supervisors, and employees implement to stimulate the prevalence of flow states during daily work activities?

First, our findings reveal that flow states emerge more frequently during some activities than others. As such, this knowledge offers important implications for practices focused on the allocation and design of work activities to stimulate flow states. Specifically, our state taxonomy can be used as an important tool to identify activities during which employees report flow and non-flow states. Organizations and supervisors can design and allocate more activities that stimulate flow based on this taxonomy. Like past research (e.g., Nielsen & Cleal, 2010), we found that examples of flow-stimulating activities include analytical and planning activities. Although allocating more flow-stimulating activities is a straightforward implication, our day reconstruction study showed that only a relatively small amount of time was spent on those activities. Because our study highlights the role of challenge appraisal in experiencing flow, organizations and supervisors could assign more activities that challenge employees and provide opportunities for growth and mastery, aligned with the conceptual definition of challenge stressors (LePine, 2022).

Not only allocating more and enhancing the time spent on challenging activities, but also reducing the time spent on hindering activities, can be an important work allocation intervention to stimulate flow states during work activities. We found that employees spend a significant amount of time performing activities that hinder flow, such as routine activities, writing emails, or attending meetings. Research has shown that such activities are more likely to result in energy depletion and demotivation and prevent employees from fully using their skills (Bakker & Oerlemans, 2019; Oerlemans & Bakker, 2018). Consistent with the Challenge Hindrance Stressors Framework, which links lower hindrance stressors to higher motivation and performance (Podsakoff et al., 2023), organizations should aim to reduce avoidable barriers to challenging and meaningful work. This can be achieved by minimizing redundant administrative activities, simplifying bureaucratic processes, and aligning required activities with employees' core responsibilities.

Second, our findings emphasize that some employees experience more flow than others. As such, not only focusing on the prevalence of flow states at the activity level, but also at the employee level, opens areas for target-specific practices and tailored interventions. Organizations could first tailor interventions primarily to ambivalent employees who rarely experience flow. Specifically, supervisors or career counselors could help those employees to identify work activities, challenges, and opportunities to grow, obtain goals, and develop their skills (Bakker & van Woerkom, 2017; Dik et al., 2015). In addition, employees who frequently experience flow can be leveraged as role models or mentors for more ambivalent employees, and the job characteristics that facilitate their flow states can be deliberately embedded into the design of ambivalent employees' jobs (cf. Liu et al., 2023).

Third, our findings highlight the importance of appraisal of work activities because these trigger how employees experience those activities (e.g., flow, anxiety, arousal). Therefore, policies or practices should aim at changing how employees appraise their work activities to enhance the prevalence of flow states. We argue that the primary aim should first be to reduce the amount of time on unchallenging or hindering activities, although each job will likely consist not only of challenging activities (Oerlemans & Bakker, 2018). Hence, supervisors and organizations could target unchallenging activities and attempt to enhance their challenge appraisal. Employees feeling bored or apathetic could be encouraged to re-appraise their activity by proactively increasing challenges (Bakker & van Woerkom, 2017). Activities could also be assigned that match employees' skill levels, or supervisors could emphasize how performing such unchallenging activities can benefit the organisation or team (Podsakoff et al., 2023).

In addition, activities perceived as hindering can be targeted for partial reappraisal where feasible. Supervisors can support this reappraisal by clarifying the purpose of such activities, linking them to broader goals, and identifying potential learning opportunities, while also working to reduce unnecessary burdens where possible. Especially during highly challenging activities that cause arousal or anxiety (Jamieson et al., 2010) and can therefore be experienced as hindering (Podsakoff et al., 2023), it could be emphasized that performing them can be an opportunity to identify ways to overcome challenges, develop skills, and ultimately perform better in the long run. Similar to the CHSF (LePine, 2022), important assumptions from flow theory are that employees should receive clear feedback and that roles during work activities should be as clear as possible to experience flow (Csikszentmihalyi, 1997). Hence, supervisors should offer clear and immediate instructions and feedback to reduce hindrance appraisal (Fullagar & Kelloway, 2009).

7. Conclusion

Studying unique constellations of the three flow components (i.e., absorption, effortless control, and intrinsic reward) to examine distinct state profiles, we found one profile that theoretically aligns with the concept of deep flow (i.e., peak levels on all three components simultaneously), while another one aligns with the concept of microflow (i.e., moderately high levels on all three components simultaneously). We found deep flow to be a relatively infrequent state for most employees in our sample. Our findings further highlight the importance of engaging in work activities perceived as challenging, rather than hindering, for deep flow to happen. Overall, this study enhances our understanding of the core nature of flow and demonstrates the benefits of setting rewarding states apart from others.

CRediT authorship contribution statement

J. De Kerf: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **D. van der Linden:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization. **R. De Cooman:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **S. De Gieter:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **A.B. Bakker:** Writing – review & editing, Resources, Methodology, Conceptualization. **J. Hofmans:** Writing – review & editing, Resources, Methodology, Formal

analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for this journal and was not involved in the editorial review or the decision to publish this article.

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Appendix A. Supplementary Tables and Figures

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jvb.2026.104246.

Data availability

The data and code used during the current study are available in the Open Science Framework repository via https://osf.io/dwufp/?view_only=85d1dc44ec0346829fee2c72050f3331.

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