*Running Head:* Longitudinal Affect Profiles

**Nature, Predictors, and Outcomes of Nurses' Affect Profiles: A Longitudinal Examination**

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**Abstract**

This study addresses the lack of organizational research considering the functionality of employees' work-related affective experiences. More precisely, this research relied on person-centered analyses to gain a better understanding of the various configurations taken by the intensity and direction (i.e., seen as facilitating performance, or as interfering with it) of positive and negative affect among nurses. We also documented the stability of these profiles over time and their longitudinal associations with theoretically relevant predictors (job demands and resources) and outcomes (somatic complaints and musculoskeletal disorders). Questionnaires were completed twice, three months apart, by a sample of 1143 French nurses. Five distinct affective profiles were identified, and found to be rather stable over time. Nurses' perceptions of their job demands and resources showed well-differentiated patterns of associations with these profiles. Finally, nurses' levels of somatic complaints and musculoskeletal disorders were more pronounced among nurses corresponding to a profile dominated by high levels of negative affect seen as interfering with performance. Overall, our results emphasize the importance of jointly considering affect intensity and direction, their combinations, and the role played by job characteristics, in order to understand the development of physical health problems among nurses.

*Keywords:* Positive and negative affect, affect intensity and direction, nurses, latent transition analysis, profiles.

## Introduction

Affective well-being is a core component of employees' psychological health (Bakker & Oerlemans, 2011). Indeed, research has reported numerous associations between employees' work-related positive and negative affective states and a variety of individual (e.g., burnout, job satisfaction, work-family issues; Sandrin et al., 2020; Zhao et al., 2019) and organizational (e.g., turnover, absenteeism, performance; Daniels et al., 2014; Sandrin et al., 2020) outcomes. Unfortunately, most research conducted in the work area has solely focused on the intensity of these positive and negative affective states, whereas recent research conducted in the sports area has documented the importance of jointly considering their directionality (Martinent et al., 2013; Martinent & Nicolas, 2016, 2017a, 2017b; Nicolas et al., 2014). This directionality pertains to the degree to which individuals perceive that their affective states can facilitate or obstruct their performance (facilitation or obstruction).

Person-centered analyses (Morin et al., 2018) are naturally suited to the joint consideration of the intensity and direction of positive and negative affective states. These analyses seek to identify discrete subpopulations (or profiles) of employees characterized by distinct configurations of affective states. Naturally aligned with managers' tendency to think of workers as corresponding to discrete categories, person-centered analyses can have important managerial implications (Meyer & Morin, 2016). Unfortunately, very little research has considered the intensity-direction distinction of affective states at work, and then only in the very specific context of fire stations (Sandrin et al., 2020). No prior study has considered the nursing context, in which positive and negative affective states play an important role in driving well-being, quality of care, and job-related outcomes (Barr, 2018; Van Bogaert et al., 2017). Yet, person-centered evidence is built upon results obtained across multiple samples, which is necessary to identify the core set of profiles that systematically appear and to distinguish them from those reflecting sample- or context- specific characteristics (Morin, 2016).

The present study thus expands upon Sandrin et al.'s (2020) study to analyze the nature and longitudinal stability of nurses' affect profiles over a period of three months. To capture the construct validity of these profiles, we consider their associations with theoretically relevant predictors and outcomes. First, we consider job characteristics (i.e., job demands and resources; Bakker & Demerouti, 2017), known to play a role in nurses' affective experiences at work (e.g., Huyghebaert et al., 2016). More precisely, we consider how specific types of job demands (physical demands and emotional load) and resources (task identity, task variety, and interdependence) relate to nurses' profile membership. Second, we consider how profile membership relates to health indicators (i.e., somatic complaints and musculoskeletal disorders), known to be prevalent among nurses (Barello et al., 2020; Ribeiro et al., 2017) and to play a key role in their psychological health, work attitudes and behaviors (e.g., burnout, turnover intentions, absenteeism; Ribeiro et al., 2017; Williams et al., 2014).

### Work-Related Affective States

Work-related affective states can be differentiated along a pleasure-displeasure continuum reflecting their hedonic valence (positive and negative) and their intensity (Watson et al., 1988). The circumplex model of affect further highlights the need to position these affective states along an activation-deactivation continuum, reflecting the extent to which these states imply high (activation) or low (deactivation) levels of arousal (Russell, 1980, 2003). Recent studies (e.g., Feuerhahn et al., 2014; Fritz et al., 2021) have demonstrated that activated affective states were most relevant when considering indicators of physical functioning, such as somatic complaints and musculoskeletal disorders. In fact, affective activation, which is directly associated with physiological arousal, is considered a core mechanism through which affective states influence physical health (Pressman & Cohen, 2005). We thus focus on activated affective states, and hereafter use the term *positive affect* to refer to activated positive affective states, reflecting "the extent to which a person feels enthusiastic, active, and alert […], a state of high energy, full concentration, and pleasurable engagement" (Watson et al., 1988, p. 1063). Conversely, we use the term *negative affect* to refer to activated negative affective states, referring to "a general dimension of subjective distress and unpleasurable engagement that subsumes a variety of aversive mood states, including anger, contempt, disgust, guilt, fear, and nervousness" (Watson et al., 1988, p., 1063).

Affective well-being is proposed to be represented by the simultaneous experience of low levels of negative affect and high levels of positive affect (Wright et al., 2009). Positive affect results in better performance (Luthans et al., 2008), including higher levels of problem-solving and patient centeredness among healthcare workers (Isen, 2001), whereas less desirable outcomes are typically associated with negative affect (Labrague & de Los Santos, 2020). Although well-documented among general populations of workers (e.g., Mäder & Niessen, 2017) these affect-outcomes associations remain under-documented in the nursing context.

Recent research conducted in the sport area have highlighted the need to move beyond this dichotomy between positive and negative affect to consider the possibility that both could be experienced as facilitating or impeding performance (Martinent et al., 2013; Martinent & Nicolas, 2016, 2017a, 2017b; Nicolas et al., 2014). Although work-related positive and negative affect tend to be aligned with similarly valenced appraisals of one's performance (Shockley et al., 2012), affective states also have different motivational and behavioral underpinnings for different individuals (Lazarus, 1991). For instance, some nurses could experience high levels of interest at work (high positive affect intensity) while feeling that this affective state hampers their job performance (low positive affect direction). Indeed, this high level of interest might push them to spend lots of time discussing with their patients or reading about new techniques and, as a result, they may fall behind on their work assignments (detrimental to performance). In contrast, these levels of interest may support the performance of other nurses who consider that having a better knowledge of their patients or new skills could help them better achieve their work. Similarly, experiencing an intense negative affect, such as being angry about the inefficacy of some procedures, may lead some nurses to withdraw from work (detrimental to performance), whereas it may push others to increase their efforts to improve the situation (facilitating performance).

Affect plays a crucial role in shaping workers' cognitions and behaviors (Barsade, 2007), so that when an individual experiences a certain affective state, this affective state may trigger specific cognitions and behaviors, which in turn influence performance (Beal et al., 2005). This emerging representation of affect suggests that the experience of positive or negative affect is automatically accompanied by an anticipation of the likely effects of this experience on performance (Martinent et al., 2013; Martinent & Nicolas, 2017b; Nicolas et al., 2014). This directional anticipation is thought to depend on primary and secondary appraisals of the affective experience, as proposed in Lazarus and Folkman's (1984) transactional theory of stress. During primary appraisal, individuals assess whether the affect is relevant for their goals and well-being, and if so, whether or not it threatens these goals and their well-being. Affective states perceived as threatening are then expected to trigger a secondary appraisal, where individuals assess whether they have enough resources to cope with this threat. Depending on these appraisals, positive and negative affect should be accompanied by distinct experiences of directionality, in which affective states come to be seen as supporting or interfering with performance. Because activated affective states involve a more active and energetic orientation (e.g., anger, hostility, enthusiasm, determination), they should be more likely to result in directional effects than passive deactivated affective states (e.g., gloominess, lethargy, calmness, contentment).

As a result, to better grasp the inextricably interrelated nature of affect intensity and direction, some have highlighted the need for future studies to rely on a person-centered approach to better understand the role played by these various affective combinations (Martinent & Nicolas, 2017a; Martinent et al., 2013; Sandrin et al., 2020). This is the approach taken in the present study.

**A Person-Centered Approach of Nurses' Affect**

Positive and negative affect intensity and direction are qualitatively distinct affective states that are not mutually exclusive but can co-occur in distinct combinations in the lives of different individuals. By focusing on affect profiles, characterized by different configurations of negative and positive affect intensity and direction, the person-centered approach is thus able to capture the true complexity of workers' affective states, which rarely involve a single emotional reaction (Gabriel et al., 2011; Larsen et al., 2017). Only a handful of studies have considered the nature of these combinations of positive and negative affect intensity and direction (Martinent & Nicolas, 2017a; Martinent et al., 2013; Sandrin et al., 2020). In the sport area, these studies converged on the identification of a common set of three profiles (Martinent & Nicolas, 2017a; Martinent et al., 2013): *Facilitators* (moderate to high positive affect intensity and average negative affect intensity, both with a facilitative effect), *Low Affect Incapacitators* (low positive affect intensity and low negative affect intensity, respectively with neutral and neutral-to-detrimental effects), and *High Negative Affect Incapacitators* (average positive affect intensity and high negative affect intensity, with respectively neutral and detrimental effects). Martinent et al. (2013) also identified a fourth profile of *High Positive Affect Facilitators*, characterized by high positive affect intensity and low negative affect intensity, respectively with a facilitative and a detrimental effect. In contrast, in the work area, Sandrin et al. (2020) identified five affect profiles among fire station employees. Most of these profiles differed from those identified in the sport area: *Low Negative Affect Facilitators* (moderately high positive affect intensity with a neutral-to-moderate facilitative effect and low negative affect intensity with a highly facilitative effect), *Moderately Low Positive Affect Incapacitators* (moderately low positive affect intensity with a very high detrimental effect and moderate negative affect intensity with a high facilitative effect), *High Positive Affect Facilitators* (high positive affect intensity with a highly facilitative effect and moderately low negative affect intensity with a moderate detrimental effect), *Very Low Positive Affect Incapacitators* (low positive affect intensity with a highly detrimental effect and high negative affect intensity with neutral effect), and *Normative* (moderate positive and negative affect intensity and direction). The *High Positive Affect Facilitators* profile is the only one identified in both areas.

These contrasting results seem to indicate that different contexts, such as the sports and work domains, can produce distinct affect configurations. This observation makes it even more important to verify which of the profiles identified by Sandrin et al. (2020), if any, are representative of those more commonly observed among other populations of workers, and which are specific to their unique sample of fire station employees. Moreover, previous studies have relied on male-dominated samples (81% in Sandrin et al., 2020; 63% in Martinent et al., 2013; 67% in Martinent & Nicolas, 2017a). Thus, in addition to increasing our understanding of affect profiles in an occupation in which affective states play an important role (Barr, 2018; Van Bogaert et al., 2017), our focus on nursing will also provide replication evidence within a traditionally female-dominated occupation. Indeed, as a result of gender socialization issues, women tend to experience more intense positive and negative affect (Brody & Hall, 2008). Moreover, affective experiences tend to be accompanied by stronger cognitions and to have stronger effects on women's behaviors, relative to men's (Scott & Barnes, 2011). As a result, one may wonder whether the profiles identified in Sandrin et al.'s (2020) male-dominated sample will generalize to a female-dominated sample of nurses. The present study thus provides a stringent test of generalizability to help us identify a core set of profiles likely to apply to multiple occupational groups, as well as additional profiles likely to be specific to some occupational groups.

Our first objective was thus to examine the generalizability of prior results by investigating the nature of the affect profiles identified in a female-dominated sample of nurses. Given the lack of prior person-centered research conducted in any female-dominated occupational group, it was difficult to propose precise hypotheses related to the number of profiles expected to be identified in the present study. Yet, when considering prior research conducted in the sport and work areas, we expect that:

***Hypothesis 1.*** *Nurses' configurations of negative and positive affect intensity and direction will be best represented by three to five profiles.*

We also expect most profiles detected in this study to match the profiles identified in previous research. More precisely, based on the nature of the profiles found in more than one previous study, we expect a *High Positive Affect Facilitators* profile (e.g., Martinent et al., 2013; Sandrin et al., 2020). Furthermore, based on previous research conducted in the sport area (Martinent et al., 2013; Martinent & Nicolas, 2017a), and on additional research showing that negative affect impedes performance more than it facilitates it (Shockley et al., 2012; Sonnentag, 2015), we expect to identify a predominantly negative profile dominated by negative affect intensity with detrimental effects on performance (*High Negative Affect Incapacitators*). In addition, considering that Sandrin et al. (2020) identified two profiles of *Low Positive Affect Incapacitators* (*Moderately Low* and *Very Low*), it seems reasonable to expect a similar profile in the present study. Furthermore, considering that previous studies identified profiles characterized by matching levels of positive and negative affect intensity (e.g., *Facilitators* and *Low Affect Incapacitators* in Martinent et al., 2013; Martinent & Nicolas, 2017a), we expect a *Mixed-Emotions* profile in the present study, although we leave as an open question whether these mixed-emotions will facilitate performance, obstruct performance, or both. Finally, considering that the largest (*Normative*) profile identified in Sandrin et al. (2020) was characterized by an average configuration, matching a similarly average dominant profile repeatedly identified in research on affective well-being at work (Morin et al., 2016a, 2017a), we also expect a similar profile. Thus:

***Hypothesis 2.*** *We expect to identify* a *High Positive Affect Facilitators* profile, a *High Negative Affect Incapacitators* profile, a *Low Positive Affect Incapacitators* profile, a *Mixed-Emotions* profile, and a *Normative* profile.

**Longitudinal Similarity and Change in Nurses' Affect Profiles**

Our second objective was to examine the extent to which the nature of the profiles, and nurses' membership into these profiles, would remain similar and stable across a three-month period. We chose this timeline based on prior research on affect (Moneta et al., 2012) suggesting that a three-month period makes it possible to go beyond daily fluctuations (Daniels et al., 2014) while remaining short enough to capture changes that might be missed over longer intervals (Wright & Shaw, 1999). Documenting the longitudinal stability of person-centered results has implications for the development of interventions tailored to distinct profiles of employees (Meyer & Morin, 2016). On the one hand, profiles that randomly fluctuate over time are likely to be useless for intervention purposes. On the other hand, profiles in which membership appears to be rigidly stable suggest that efforts to help employees adopt more desirable profiles are likely to be difficult.

When considering the longitudinal stability of person-centered results, two components are important to consider: Within-sample stability and within-person stability (Gillet et al., 2017). Within-sample stability refers to the extent to which the number (configural similarity) and nature (structural similarity) of the profiles remain stable over time (Morin et al., 2016b). A lack of within-sample stability suggests that profiles reflect an ephemeral phenomenon and can therefore not be relied upon to guide interventions. Within-sample stability also refers to the extent to which members of specific profiles remain more or less similar to one another over time (dispersion similarity) and to the degree to which each profile's size remains unchanged (distributional similarity; Morin et al., 2016b). Although less important for intervention purposes, these last forms of within-sample similarity provide a more stringent test of replicability than the sole focus on the first two forms of similarity. In contrast, within-person stability reflects whether individuals' profile membership remains stable over time. This form of stability is particularly important because affective states are known to fluctuate within individuals (Weiss & Cropanzano, 1996), including nurses (Gabriel et al., 2011).

In the only prior longitudinal person-centered examination of the four components of work-related affect, Sandrin et al. (2020) found a very high level of within-sample stability over a period of four months. They also reported very high levels of within-person stability for three of their five profiles. However, their results also indicated that two profiles (i.e., *Low Negative Affect Facilitators* and *Moderately Low Positive Affect Incapacitators*), both characterized by high levels of negative affect direction (i.e., negative affect seen as supporting performance), were characterized by frequent transitions over time, thus suggesting that high negative affect direction might be hard to sustain over time. Based on previous evidence, we thus expect:

***Hypothesis 3****. The profiles will display a high level of within-sample stability (i.e., configural, structural, dispersion, and distributional similarity).*

***Hypothesis 4****. Profile membership will be characterized by a high level of within-person similarity for most expected profiles. However, should a profile characterized by high level of negative affect direction be identified, this profile should display a lower level of within-person stability.*

**Predictors of Nurses' Affect Profiles**

The third objective of this study was to assess the extent to which nurses' job characteristics predicted their profile membership. Affective events theory proposes that the way employees perceive their work environment is a proximal cause of their affective states (Weiss & Cropanzano, 1996). In this regard, the *Job Demands-Resources* (JD-R) theory notes that most job characteristics can be categorized as either job demands or resources (Bakker & Demerouti, 2017). Job demands "refer to those physical, social, or organizational aspects of the job that require sustained physical or mental effort" (p. 274), whereas job resources "refer to those physical, psychological, social, or organizational aspects of the job that are functional in achieving work goals" (p. 274). Research anchored in the JD-R theory has confirmed that job demands and resources were strongly related to employees' affective experiences (Bakker & Demerouti, 2017). Yet, these studies have solely explored affect intensity, leading some to call for future research to further document the conditions (i.e., job demands and resources) that generate affective experiences and facilitate performance (Bakker & Demerouti, 2017).

Physical and emotional demands are recognized among the main job demands for nurses (McVicar, 2003). Nurses often have to carry or move heavy weights (patients; equipment), adopt unnatural body postures (bending; reaching), walk considerable distances within a typical workday (across and up/down hospital floors), and complete all of these actions in a hasty manner with little time to recuperate or stretch in between. These physical demands are likely to result in negative emotions resulting from the impression that no matching effort is made by their workplace to facilitate this aspect of their work

(Nelson et al., 2006), making it less likely for these negative emotional states to be viewed as facilitating performance. Moreover, nursing is an emotionally demanding profession, as nurses have to face the pain of their patients on a daily basis, in addition to being frequently confronted with incivilities from patients and their families and to experiencing emotionally demanding conflicts with their peers or supervisors/medical staff. Interestingly, emotional demands have been associated with reduced affective well-being in working populations (Virtanen et al., 2021), including healthcare professionals (Bakker & Heuven, 2006; Xanthopoulou et al., 2007). Indeed, emotional demands are typically considered hindrances that trigger negative emotional arousal, coupled with reduced performance (Tadić et al., 2015). Yet, no research has ever examined either of these job demands in relation to affect direction, or to affective states defined based on the intensity-direction combination. Based on the aforementioned rationale, we expect that:

***Hypothesis 5.*** *Physical and emotional demands will predict membership into profiles characterized by higher levels of negative affect intensity with a detrimental effect on performance.*

Job characteristics such as task identity (i.e., "the degree to which a job involves a whole piece of work", Morgeson & Humphrey 2006, p. 1323), task variety (i.e., "the degree to which a job requires employees to perform a wide range of tasks on the job", Morgeson & Humphrey 2006, p. 1323), and interdependence (i.e., "the extent to which a job is affected by work from other jobs", Morgeson & Humphrey 2006, p. 1324) are generally acknowledged as key drivers of employees' work-related affect (Spector & Jex, 1991). Indeed, such job resources are proposed to make one's job more motivating and enjoyable (Morgeson & Humphrey, 2006), leading to more positive affect, less negative affect, and higher subjective performance (Humphrey et al., 2007). However, because nurses often have to complete their work in an understaffed context (Aiken et al., 2013), the task characteristics of their job may be blurred (e.g., task identity, task variety) and the interdependent nature of their job (i.e., the need to work collaboratively) may be severely tested, making it particularly important to consider the role played by these job resources. We expect that:

***Hypothesis 6***. *Task identity, task variety, and interdependence will predict membership into profiles characterized by higher levels of positive affect intensity with a facilitative effect on performance.*

**Outcomes of Nurses' Affect Profiles**

Our final objective was to document the health implications (musculoskeletal disorders and somatic complaints) of nurses' affect profiles. These two types of health-related difficulties are particularly prevalent in nursing (Barello et al., 2020; Ribeiro et al., 2017), possibly because of the aforementioned demands that are associated with this occupation. Verifying whether affect profiles could contribute to prevent the emergence of these health-related difficulties could thus be highly relevant to the design of preventive interventions. Prior research on affect intensity has supported the suggestion of "affect symmetry", wherein positive affect is associated with positive consequences and negative affect relates to negative outcomes (Sonnentag, 2015). However, no research has yet verified the relations between the intensity and direction of affective states and health outcomes. In fact, scholars have recently called for research to examine the relations between affective well-being and physical health indicators (Bakker & Demerouti, 2017), suggesting that the affective outcomes (e.g., affect profiles) of job demands (e.g., emotional and physical demands) and resources (e.g., task identity and variety, interdependence) could be involved in the development of physical complaints.

Although affective experiences are an indicator of short-term levels of well-being (Diener et al., 2006), affective events theory (Weiss & Cropanzano, 1996) suggests that their accumulation could yield long-term consequences. Indeed, positive and negative affective experiences are proposed to reflect distinct biobehavioral systems (Sonnentag, 2015): Negative affect arouses individuals' autonomic nervous system and produces increases in blood pressure or heart rate, whereas positive affect is associated with a return to baseline levels of cardiovascular activation, lower cortisol, and reduction in physical pain (Fredrickson et al., 2000; Steptoe et al., 2005).

The experience of negative affect has been identified as an important predictor of somatic symptoms in various populations (Watson, 1988), including nurses (De Gucht et al., 2003). There is an important psychological component to these symptoms, which reflect physical manifestations experienced by a person (e.g., headaches, sleeping problems) that are difficult to verify through medical assessment procedures and for which a physical cause can rarely be identified (Spector & Jex, 1998). For instance, negative emotions (intensity) and reduced performance (direction) at work may be accompanied by ruminative thoughts, which could translate into physical symptoms such as sleeping problems, headaches, loss of appetite, and stomachaches (Kinnunen et al., 2017).

Research has also identified associations between work-related affective states and musculoskeletal disorders (Kottwitz et al., 2017). Indeed, affective states often have important cognitive implications (Fredrickson, 2000), including an impact on pain perceptions (Crofford, 2015). Thus, persistent negative emotions may become pathological, whereas positive emotions may serve homeostatic purposes, allowing the organism to maintain or return to a state of physiological equilibrium (Vie et al., 2012). The psychological strain inherent to negative experiences (e.g., negative affect intensity and direction) may translate into increased tension and pain in the upper body, shoulders, and back (i.e., musculoskeletal disorders; Pekkarinen et al., 2013). Based on these various sources of evidence, and the acknowledgment that when it comes to affective experiences “bad is stronger than good” (Baumeister et al., 2001; Watson, 1988), we expect that:

***Hypothesis 7.*** *Somatic complaints and musculoskeletal disorders will be more severe in profiles characterized by higher levels of negative affect intensity with a detrimental effect on performance.*

# Method

## Participants and Procedure

Nurses were invited to take part in this study through a large recruitment campaign conducted among various healthcare institutions located in France. This invitation explained the general purpose of the study and its longitudinal nature. At each of the two data collection points, 3 months apart, nurses were assured of the voluntary and anonymous (through an identification code) nature of their participation, which was based on informed consent. Completed questionnaires were returned to the research team either through prepaid envelopes or sealed boxes. A total of 1143 French nurses ($M_{age}$ = 41.12 years; *SD* = 11.08; 81.01% women) completed the survey at Time 1. Participants had an average job tenure of 13.87 years (*SD* = 10.98), most of them worked full-time (69.55%) and had a permanent contract (87.31%).

Among the 1143 participants who completed the questionnaire at Time 1, 388 (33.95 %) also took part in the study at Time 2. Similar rates of retention have been reported in previous longitudinal studies conducted among French nurses (e.g., 27.7% in Huyghebaert-Zouaghi et al., 2020) or other occupational groups exposed to high workload (e.g., Houle et al., 2020: 33.9%). This rate of attrition thus seems to reflect the highly demanding nature of the nursing occupation, where inadequate staffing and resources combine with austerity measures to generate substantial levels of work overload (Gillet et al., 2020). This work overload is likely to explain why many nurses were unable to find time to complete the Time 2 questionnaire. Moreover, at least in France, nurses are often moving across institutions' floors and do not have access to a dedicated work computer, which could have further complicated their ability to participate at Time 2 during their work hours. Lastly, no incentive, sponsorship, personalization or other types of response-enhancing techniques (Anseel et al., 2010) were used in this study, which could have contributed to this moderate rate of retention. Attrition analyses revealed that the likelihood of attrition was weakly correlated with participants’ age ($r$ = -.077) and tenure ($r$ = -.082), as well as with their positive ($r$ = .092) and negative ($r$ = .070) affect intensity, and positive affect direction ($r$ = -.157), but not to any other variable used in this study.

## Material

All measures were administered in French at both waves. Instruments not already available in this language (i.e., somatic symptoms and musculoskeletal disorders) were adapted using a standard translation back-translation procedure (e.g., Beaton et al., 2000).

**Job demands.** Emotional load was measured using a four-item subscale (e.g., « Does your work demand a lot from you emotionally? »; $\alpha_{T1}$ = .697, $\alpha_{T2}$ = .756) developed in French by Lequeurre et al. (2013). Responses were rated on a seven-point frequency scale (1- never to 7- always). Physical demands were assessed using a three-item subscale (e.g., « This job involves important physical effort »; $\alpha_{T1}$ = .880, $\alpha_{T2}$ = .902) validated in French by Bigot et al. (2013) and rated on a seven-point agreement scale (1- strongly disagree to 7- strongly agree).

**Job resources.** Three subscales, developed in French by Bigot et al. (2013), were used to measure task variety (4 items ; e.g., « This job involves a wide variety of tasks »; $\alpha_{T1}$ = .884, $\alpha_{T2}$ = .888), task identity (four items ; e.g., « This job is arranged so that I can do an entire piece of work from beginning to end »; $\alpha_{T1}$ = .799, $\alpha_{T2}$ = .862), and interdependence (three items ; e.g., « My work activities strongly depend on the work of others »; $\alpha_{T1}$ = .737, $\alpha_{T2}$ = .747). These items were rated on a seven-point agreement scale (1- strongly disagree to 7- strongly agree).

**Work-related affect.** Positive and negative affect intensity and direction were assessed using the measure previously used by Sandrin et al. (2020), who provided evidence for the reliability, factor validity, longitudinal invariance, and temporal stability of scores obtained on this measure. Essentially, this measure incorporates the items from the French version of the Positive and Negative Affect Schedule (Watson et al., 1988), to which a directional component was added based on work conducted by Nicolas et al. (2014) in the sport area. Following from previous studies (Feuerhahn et al., 2014; Fritz, et al., 2021) only the items referring to activated affective states were included in this study. Four items each were used to assess positive (e.g., "enthusiastic"; intensity: $\alpha_{T1}$ = .595, $\alpha_{T2}$ = .659; direction: $\alpha_{T1}$ = .726, $\alpha_{T2}$ = .717) and negative (e.g., "nervous"; intensity: $\alpha_{T1}$ = .517, $\alpha_{T2}$ = .654; direction: $\alpha_{T1}$ = .757, $\alpha_{T2}$ = .833) work-related affective states. For each item, participants were asked to indicate the intensity of their affective experience at work using a five-point response scale (1- not at all to 5- extremely) and the extent to which this affective state had an impact on the quality of their work (1- very detrimental to 7- very favorable).

**Somatic symptoms.** Four items from the Physical Symptom Inventory (PSI; Spector & Jex, 1998) were used to assess nurses' somatic complaints ($\alpha_{T1}$ = .688, $\alpha_{T2}$ = .675). Nurses were asked to indicate how often they had experienced each symptom (headaches, sleeping problems, loss of appetite, and an upset stomach or nausea) over the past month using a five-point scale (1- not at all to 5- every day).

**Musculoskeletal disorders.** The eight-item version of the Nordic Musculoskeletal Questionnaire (Pekkarinen et al., 2013) was used. Nurses were asked to indicate the number of days they had experienced pain in distinct areas (neck, shoulder, elbow, wrists or hands, hips, knees, and back) in the last three months using a five-point scale (1-none, 2- one to seven days, 3- eight to 30 days, 4- over 30 days but not on a daily basis, and 5- every day). Following Pekkarinen et al (2013), respondents who reported frequent pain on each item separately (i.e., over 30 days in the last three months or every day) were identified as suffering from musculoskeletal disorders (coded 0- no musculoskeletal disorder, and 1- musculoskeletal disorder), resulting in a binary coding for all items.

## Analyses

### Preliminary Measurement Analyses

We first verified the psychometric properties and measurement invariance over time (Millsap, 2011) of all measures used in the present research. The specification of all models used as part of these preliminary analyses (i.e., measurement models and invariance over time) are disclosed in the online supplements. To ensure that the time-specific measures used in the main study could be considered fully comparable across time points, factor scores were saved from the most longitudinally invariant measurement models and used as input for the main analyses. These factor scores were estimated in standardized units ($M$= 0; $SD$= 1). Factor scores have the advantage of preserving the measurement structure of the model (e.g., invariance; Morin et al., 2016a, 2016b) and are partially corrected for unreliability (Skrondal & Laake, 2001).

### Latent Profile Analyses (LPA)

Second, time-specific LPA models including 1 to 8 profiles were estimated using the four affect factor scores as profile indicators and allowing the mean of these indicators to vary across profiles. These analyses were used to verify whether the same number of profiles would be identified across time points. These LPA were estimated using 5000 sets of random start values (e.g., Hipp & Bauer, 2006), each allowed 1000 iterations and 200 final stage optimizations. Although there are advantages to allow for the free estimation of indicators' variance across profiles (Peugh & Fan, 2013), these models were associated with convergence issues (e.g., nonconvergence, improper parameter estimates), suggesting overparameterization and the need to rely on more parsimonious models in which these variance parameters were not allowed to differ across profiles (Morin & Litalien, 2019). Assuming that the same number of profiles were estimated across time points, the two time-specific LPA solutions were then incorporated into a single longitudinal LPA model. This model was then used to conduct tests of profile similarity (Morin et al., 2016b; Morin & Litalien, 2017): (a) *configural* similarity (i.e., same number of profiles over time); (b) *structural* similarity (i.e., same within-profile means); (c) *dispersion* similarity (i.e., same within-profile variances); and (d) *distributional* similarity (i.e., same profile size).

### Latent Transitions Analyses (LTA)

The most similar longitudinal LPA solution was then re-expressed into a LTA model to examine within-person stability and transitions (Kam et al., 2016). This LTA solution, as well as all subsequent analyses, was built from the most similar longitudinal LPA solution identified previously, and converted to a LTA using the manual 3-step approach (Asparouhov & Muthén, 2014) following procedures outlined by Morin and Litalien (2017).

**Predictors**

The associations between the time-specific predictors (job demands: physical demands, emotional load; and job resources: task identity, task variety, and interdependence) and profile membership were evaluated via a multinomial logistic regression link function following the direct incorporation of the predictors into the LTA. Three models were contrasted (Morin & Litalien, 2019). First, the effects of the predictors were estimated freely across time points and Time 1 profiles to test whether predictors explained specific profile transitions. Second, these effects were allowed to differ over time but not across Time 1 profiles. In a third model, these effects were constrained to be equal across time points and Time 1 profiles (predictive similarity).

**Outcomes**

Time-specific outcome measures (i.e., somatic symptoms, musculoskeletal disorders) were integrated into the final LTA to assess their associations with the profiles measured at the same time point. In a first model, these associations were allowed to differ over time, whereas they were constrained to equality over time in a second model (*explanatory similarity*). Mean-level differences were estimated in a single step using the multivariate delta method (Raykov & Marcoulides, 2004), implemented using the MODEL CONSTRAINT function (e.g., Morin & Litalien, 2019).

**Model Estimation**

The maximum likelihood robust (MLR) estimator implemented in Mplus 8 (Muthén & Muthén, 2021) was used to realize all of our main analyses, using full information Maximum Likelihood (FIML) procedures (Enders, 2010) to handle missing data. FIML relies on missing at random (MAR) assumptions, allowing missing values to be conditioned on all variables included in the analytical model, which includes the variables themselves measured at different time points in longitudinal analyses. FIML is known to be as effective as multiple imputation, even in the presence of a large amount of missing data (e.g., 70%+; Enders, 2010; Jeličič et al., 2009; Larsen, 2011; Lee et al., 2019; Newman, 2003), making it possible to estimate longitudinal models using responses from all participants, rather than relying on the problematic listwise deletion of participants who only completed a single time wave. Given their similar efficiency, FIML is generally recommended over multiple imputation when working with complex models due to its greater computational simplicity (e.g., Enders, 2010; Graham, 2009). Moreover, multiple imputation is generally not recommended for person-centered analyses given that it would require the aggregation of the best loglikelihood value obtained across each imputation, even though each of those values might correspond to a completely different solution. It should be noted that FIML is not an imputation method (no values are estimated to replace the missing responses).

**Model Selection and Comparisons**

Multiple sources of information were used to decide how many profiles should be retained at each time point to test Hypothesis 1. More precisely, we considered their meaningfulness, theoretical relevance, and statistical adequacy (Marsh et al., 2009). Several statistical indicators were also consulted to guide this decision (McLachlan & Peel, 2000). More precisely, lower values on the Akaïke Information Criterion (AIC), Consistent AIC (CAIC), Bayesian Information Criterion (BIC), and sample-size Adjusted BIC (ABIC) indicate better fitting models. In addition, statistically significant results on the Lo, Mendell and Rubin's (2001) Likelihood Ratio Test (aLMR) and Bootstrap Likelihood Ratio Test (BLRT) support a model relative to one including fewer profiles. Prior statistical research revealed that the BIC, CAIC, ABIC, and BLRT, but not the AIC and aLMR, were efficient at helping to identify the number of latent profiles (e.g., Diallo et al., 2016, 2017; Peugh & Fan, 2013). For this reason, the AIC and aMLR will not be used, and will only be reported for purposes of transparency. However, because these tests present a strong sample size dependency (Marsh et al., 2009), they often fail to converge on a specific number of profiles. When this happens, it is recommended to rely on a graphical display of these indicators (or elbow plot), in which the observation of a plateau may help to pinpoint the optimal solution (Morin & Litalien, 2019). We also report the entropy, as a descriptive indicator of classification accuracy (ranging from 0 to 1).

In relation to Hypothesis 2, profiles are typically interpreted in a holistic manner, based on the overall configurations of scores obtained on their indicators (positive and negative affect intensity and direction) (Morin & Meyer, 2016; Morin et al., 2018). To assess whether the profiles matched Hypothesis 2, we considered whether the affect indicators matched the levels of intensity (high, moderate, low in relation to the sample mean) and direction (facilitation, neutral, incapacitation in relation to the sample mean) found in the previous studies used to guide this hypothesis.

For tests of within-sample profile similarity designed to test Hypothesis 3, lower values on at least two of the CAIC, BIC, and ABIC can be used to support a more similar model relative to the previous one in the sequence (Morin et al., 2016b). Lastly, in relation to Hypothesis 4, it is important to clarify that no formal guideline exists, or should exist, to guide the interpretation of what represents high, low, or moderate rates of within-person stability. To some extent, these interpretations will always vary across studies depending on the time interval, the inherent stability in the constructs modelled by the indicators, but also on the relative stability of all profiles. As a rough guideline, considering that the present study relies on a relatively short time interval (three months) and on a construct that is known to fluctuate moderately over time (i.e., affect intensity and direction), we tentatively suggest that rates approaching 50% would reflect moderate levels of within-person stability in profile membership, whereas rates closer to 70% or higher to would reflect high levels of stability. We caution readers, however, about blindly adopting such guidelines, and reinforce that we do not see such guidelines as necessary to the interpretation of LTA.

## Results

### Preliminary Measurement Analyses

The results from the preliminary analyses (measurement models, measurement invariance over time, composite reliability, and correlations) are reported in the online supplements. More specifically, the goodness-of-fit and parameter estimates of the affect measurement models are reported in Table S1 and S2, those associated with the predictor measurement models are reported in Tables S3 and S4, and those associated with the outcomes measurement models are reported in Tables S5 and S6. These results supported the psychometric adequacy (i.e., model fit, parameter estimates, reliability), as well as the complete measurement invariance, of all solutions. More precisely, the composite reliability of all factors (ω; McDonald, 1970) ranged from .659 to .692 for positive affect intensity, from .670 to .752 for negative affect intensity, from .766 to .783 for positive affect direction, from .829 to .875 for negative affect direction, from .886 to .889 for task variety, from .812 to .867 for task identity, from .754 to .766 for interdependence, from .888 to .910 for physical demands, from .710 to .767 for emotional demands, from .780 to .787 for somatic symptoms, and from .836 to .872 for musculoskeletal disorders. Pairwise correlations among all variables (i.e., factor scores and observed demographics) are reported in Table S7 and supported the distinctiveness of all constructs.

### Latent Profile Analyses (LPA)

The results from the Time-specific LPA solutions are reported in Table 1. Across time waves, the information criteria and BLRT kept on suggesting the addition of profiles. As a result, we examined elbow plots reported in Figures S1 and S2 of the online supplements. This examination suggested, at both time points, a slight inflection located around six profiles, leading us to examine solutions including five to seven profiles. This examination revealed that these solutions were highly similar across time points. Furthermore, when solutions including increasing numbers of profiles were compared, the additional profiles resulted in a meaningful contribution to the solution up to the five-profile solution (moving from four to five profiles resulted in the addition of a profile corresponding to the second one illustrated in Figure 1 at Time 1 and to the fifth one at Time 2, and thus providing early evidence of profile similarity). In contrast, adding a sixth, or seventh, profile to the solution only led to the arbitrary division of an existing profile into smaller ones characterized by a similar shape. Based on this examination, the five-profile solution was retained at both time points, thus supporting its configural similarity and Hypothesis 1.

These two time-specific LPA solutions where then combined into a single longitudinal LPA of configural similarity. Results from the further tests of similarity conducted on this solution are reported in Table 2. These results first indicated that the solution of structural similarity was not supported (as indicated by higher values on the CAIC, BIC, and ABIC relative to the model of configural similarity), consistent with differences occurring over time in the shape of the profiles. A careful examination of the freely estimated parameters from the solution of configural similarity suggested that this lack of structural similarity could be limited to very small differences (ranging from .02 to .20 SD) on two indicators (positive and negative affect intensity) of the fifth profile. Allowing the within-profile means of these two indicators to be freely estimated across time points in the fifth profile resulted in a solution of partial structural similarity (Morin et al., 2016b) that was supported by the data (lower values on the

CAIC and BIC relative to the model of configural similarity). The next model of dispersion similarity also failed to be supported (higher values on the AIC, BIC, and ABIC relative to the model of partial structural similarity), indicating differences related to within-profile variability. A careful examination of the freely estimated parameters associated with all previous solutions suggested that this difference could be limited to the last two profiles (which did not differ from one another at any time point), characterized by a slightly lower level of within-profile variability on all indicators at Time 2 relative to all other profiles at both time points. Relaxing these constraints resulted in a solution of partial dispersion similarity that was supported by the data (lower values on the CAIC, BIC, and ABIC relative to the model of partial structural similarity). The next solution of distributional similarity was also supported by the data (lower values on the CAIC and BIC relative to the model of partial dispersion similarity), indicating that the size of the profiles did not change over time.

The results from this model are illustrated in Figure 1, and parameter estimates are reported in Table S8 of the online supplements. Profile 1 presented very high levels of positive affect intensity with a highly detrimental effect and high levels of negative affect intensity with a neutral-to-facilitative effect. This profile, labelled "*Intense Mixed Emotions Incapacitators*", corresponded to 6.21% of the sample. Profile 2 presented moderate levels of positive and negative affect intensity, the former with a highly detrimental effect and the latter with a neutral-to-detrimental effect. This "*Mixed Emotions Incapacitators*" profile characterized 10.39% of the sample. Profile 3 presented low levels of positive affect intensity with a moderately detrimental effect, and by high levels of negative affect intensity with a moderately detrimental effect. This "*High Negative Affect Incapacitators*" profile corresponded to 14.75% of the participants. Profile 4 presented moderate levels of positive and negative affect intensity, both of which with close to neutral (neutral-to-facilitative for positive affect, and neutral-to-detrimental for negative affect) effects. This "*Normative*" profile was also the largest, corresponding to 53.90% of the participants. Finally, Profile 5 presented moderate levels of positive affect intensity and a moderately high facilitative effect, and low levels of negative affect intensity with a high facilitative effect. This "*Low Negative Affect Facilitators*" profile corresponded to 14.76% of the participants. These results partially support Hypothesis 2.

As shown in Figure 1, the difference in the structure of the fifth profile occurring over time remained negligible, suggesting slightly lower levels of positive affect intensity and slightly higher levels negative affect intensity at Time 2. These slight differences, as well as the similarly slight differences in variances (see Table S8 of the online supplements) are small enough to suggest that they reflect random sampling variations due to the lower sample size available at Time 2. We conducted additional analyses to assess whether participants' likelihood of membership into the various profiles was related to their likelihood of attrition. These correlations were all very small ($r$ = .059 to .189) and were all consistent with the MAR process used in FIML as these profiles (i.e., the latent categorical variables representing them and participants' likelihood of membership into these profiles) were part of all analyses.

**Latent Transitions Analyses (LTA)**

The transition probabilities from the LTA solution built from the final longitudinal LPA are reported in Table 3. These results indicated that membership into Profiles 2 (*Mixed Emotions Incapacitators*, stability of 100%) and 3 (*High Negative Affect Incapacitators*, stability of 100%) was perfectly stable over time, indicating that none of the nurses initially corresponding to this profile displayed a different profile at Time 2. Likewise, membership into Profiles 1 (*Intense Mixed Emotions Incapacitators*: stability of 85.2%) and 4 (*Normative,* stability of 96.4%) was also very stable over time, although transitions out of these profiles also occured. More precisely, 14.8% of nurses initially corresponding to Profile 1 transitioned into Profile 2 (*Mixed Emotions Incapacitators*) at Time 2, whereas 3.6% of the nurses initially corresponding to Profile 4 transitioned toward Profile 5 (*Low Negative Affect Facilitators*) at Time 2. Finally, Profile 5 was the least stable (*Low Negative Affect Facilitators*; Stability of 59.8%), involving transitions toward Profiles 3 (1.6%: *High Negative Affect Incapacitators*) or 4 (38.6%: *Normative*). Overall, these results support Hypotheses 3 and 4.

**Predictors**

The results from the alternative predictive models are reported in Table 2. These results supported the model of predictive similarity (lowest values for the CAIC, BIC, and ABIC relative to the other models), indicating that predictions were unchanged over time. However, they also indicated that this role was not moderated by Time 1 profile membership (i.e., predictors did not influence specific transitions). Estimates from this model of predictive similarity are reported in Table 4.

In relation to job resources, the results first revealed that higher levels of task identity were related to a higher likelihood of membership into Profiles 1 (*Intense Mixed Emotions Incapacitators*), 2 (*Mixed Emotions Incapacitators*) and 4 (*Normative*) relative to Profile 3 (*High Negative Affect Incapacitators*), as well as into Profile 5 (*Low Negative Affect Facilitators*) relative to Profiles 2 (*Mixed Emotions Incapacitators*), 3 (*High Negative Affect Incapacitators*), and 4 (*Normative*). Second, higher levels of task variety were related to a higher likelihood of membership into Profile 4 (*Normative*) relative to Profiles 3 (*High Negative Affect Incapacitators*) and 2 (*Mixed Emotions Incapacitators*). Finally, higher levels of interdependence were associated with a higher likelihood of membership into Profile 5 (*Low Negative Affect Facilitators*) relative to Profile 4 (*Normative*). These results generally support Hypothesis 6.

In relation to job demands, the results first revealed that higher levels of emotional load were associated with a higher likelihood of membership into Profiles 2 (*Mixed Emotions Incapacitators*), 3 (*High Negative Affect Incapacitators*), and 4 (*Normative*) relative to Profile 5 (*Low Negative Affect Facilitators*), as well as into Profiles 2 (*Mixed Emotions Incapacitators*) and 3 (*High Negative Affect Incapacitators*) relative to Profile 4 (*Normative*). Higher levels of emotional load were also associated with a higher likelihood of membership into Profile 2 (*Mixed Emotions Incapacitators*) relative to Profile 1 (*Intense Mixed Emotions Incapacitators*). Second, higher levels of physical demands were associated with a higher likelihood of membership into Profile 5 (*Low Negative Affect Facilitators*) relative to Profiles 1 (*Intense Mixed Emotions Incapacitators*), 2 (*Mixed Emotions Incapacitators*), and 4 (*Normative*), as well as into Profile 4 (*Normative*) relative to Profiles 1 (*Intense Mixed Emotions Incapacitators*) and 2 (*Mixed Emotions Incapacitators*). Furthermore, higher levels of physical demands were associated with a higher likelihood of membership into Profile 3 (*High Negative Affect Incapacitators*) relative to Profiles 1 (*Intense Mixed Emotions Incapacitators*) and 2 (*Mixed Emotions Incapacitators*), as well as into Profile 1 (*Intense Mixed Emotions Incapacitators*) relative to Profile 2 (*Mixed Emotions Incapacitators*). These results generally support Hypothesis 5.

**Outcomes**

The results from the alternative outcome models are reported in Table 2 and support the model of explanatory similarity (lowest values for the CAIC, BIC, and ABIC relative to the other models), showing that these associations generalize over time. The results from this model are reported in Table 5 and revealed few differences. More precisely, levels of somatic symptoms and musculoskeletal disorders were higher in Profile 3 (*High Negative Affect Incapacitators*) than in all other profiles, which did not differ from one another. These results generally support Hypothesis 7.

## Discussion

This study was designed to answer a call for a more integrative consideration of the intensity and direction of positive and negative affective states (Martinent et al., 2013; Martinent & Nicolas, 2017b; Nicolas et al., 2014; Sandrin et al., 2020), as applied to the work context (Sandrin et al., 2020). In fact, a single study had previously considered the configurations, or profiles, of work-related affective states, but in the unique context of male-dominated fire stations (Sandrin et al., 2020). The present study provides replication evidence in a female-dominated sample of nurses, whose affective states are known to be of particular importance (e.g., Barr, 2018; Van Bogaert et al., 2017). Furthermore, we also examined the longitudinal within-sample and within-person stability of these profiles over a period of three months, the role played by job demands and resources in the prediction of profile membership, and the implications of these profiles in relation to health-related consequences. We more extensively discuss these contributions and their implications in the following pages.

**Theoretical and Practical Implications**

***On the Nature and Stability of Nurses' Affect Profiles***

Although prior studies have demonstrated that affective states (i.e., affect intensity) and efficacy beliefs (i.e., affect direction) were interrelated among nurses (e.g., Lehmann et al., 2020), they have failed to consider the possibility that these components could combine in different manners among different profiles of nurses. Our research took a step forward by examining these profiles in a sample of nurses, while expanding upon prior research conducted among firefighters (Sandrin et al., 2020). However, unlike this previous study (Sandrin et al., 2020), we relied on a shorter measure of affect intensity and direction focusing solely on activated affects, expected to have a stronger directionality. Supporting our expectations, our results revealed five profiles of nurses characterized by distinctive configurations of affective states: 1) *Intense Mixed Emotions Incapacitators*; 2) *Mixed Emotions*

*Incapacitators*; 3) *High Negative Affect Incapacitators*; 4) *Normative*; and 5) *Low Negative Affect Facilitators.* Moreover, in their previous study of nurses, Lehmann et al. (2020) showed that the valence of affect intensity (i.e., positive *versus* negative) was the only significant predictor of efficacy beliefs (i.e., affect direction), suggesting that affect direction is not a matter of activation but rather a matter of valence. In line with this suggestion, two profiles identified in this study (*Normative* and *Low Negative Affect Facilitators*) were consistent with those identified by Sandrin et al. (2020), suggesting that these profiles might be independent of the activated nature of affective states. In contrast, the remaining profiles (*Intense Mixed Emotions Incapacitators, Mixed Emotions Incapacitators* and *High Negative Affect Incapacitators*) did not match those identified in Sandrin et al. (2020), suggesting that these profiles (especially those characterized by mixed emotions), might be easier to detect while focusing on activated affective states, although they might also reflect the distinctiveness of the nursing occupation. These observations might have important implications in a context where researchers often chose to focus solely on activated affect (e.g., Feuerhahn et al., 2014; Fritz et al., 2021), and clearly deserve more attention in the context of future research.

First, it was particularly interesting to identify a dominant (corresponding to slightly more than half of the sample) *Normative* profile of nurses, characterized by an average intensity of positive and negative affect, with a mainly neutral direction. This profile matched one previously identified by Sandrin et al. (2020), as well as similar profiles identified in research on affective well-being at work (Morin et al., 2016a, 2017a). This result thus suggests that, in the work area, a small majority of employees, across work contexts and occupations, seems able to keep their affective states in check without allowing them to influence, positively or negatively, their performance.

Second, the *High Negative Affect Incapacitators* profile, dominated by high levels of negative affect intensity with detrimental effects on performance, matched results obtained in the sport area (Martinent et al., 2013; Martinent & Nicolas, 2017a), suggesting that this type of profile may occur in both contexts. However, this profile was less common (close to 15%) in the nursing context than in the sport context (15% to 20%; Martinent et al., 2013; Martinent & Nicolas, 2017a). This profile is also consistent with research indicating that predominantly negative affective states tend to exert a detrimental effect on performance (Shockley et al., 2012; Sonnentag, 2015).

Third, we identified a *Low Negative Affect Facilitators* profile, characterized by low negative affect intensity with a facilitative effect on performance. Although unexpected (given that we anchored our expectations based on profiles identified more than once in previous research), a similar profile was previously reported by Sandrin et al. (2020). This observation, coupled with the fact that none of the studies conducted in the sports area identified a similar profile, suggests that this profile might be specific to the work context, but likely to generalize across different occupational and organizational contexts. Importantly, this result suggests that, at work, at least some employees (close to 15% in the nursing context relative to less than 10% among fire station employees) appear to benefit from the experience of low levels of negative affect.

Fourth, and even though two profiles matching this configuration were observed by Sandrin et al. (2020), our results failed to identify a *Low Positive Affect Incapacitators* profile. This result thus suggests that these profiles might be sample- or context- specific, and possibly highly relevant for some organizational (e.g., fire stations) or occupational contexts but not for other contexts (nursing). However, it is important to acknowledge that, in Sandrin et al.'s (2020) study, this profile appeared to be relatively rare, corresponding to less than 6% of employees. Clearly, future research will be needed to better document the conditions under which such a profile is more likely to emerge, and its specific implications for employees' performance, attitudes, and health.

Fifth, despite the fact that a *High Positive Affect Facilitators* profile was previously identified in the sports (close to 30% of participants in Martinent et al., 2013) and work (close to 25% of employees in Sandrin et al., 2020) areas, a similar profile was not identified in the current sample of nurses. This result may be due to the demanding nature of the nursing occupation, characterized by frequent exposure to suffering and death, understaffing, inadequate resources, and austerity measures (Aiken et al., 2013), which may make it harder for nurses to experience predominantly positive affective experiences at work. Clearly, replication evidence will be needed to better understand the conditions that favor, or limit, the occurrence of this profile.

Sixth, in line with the previous observation that the experience of predominantly positive affective states might be less frequent among nurses, we identified two profiles characterized by the simultaneous experience of high, or very high, levels of both positive and negative affect intensity (*Intense Mixed Emotions Incapacitators* and *Mixed Emotions Incapacitators*). Moreover, in both profiles, affective states were seen as interfering with performance. These configurations could reflect the fact that, for roughly 15% of nurses, positive affective experiences (e.g., feeling enthusiastic about patients' recovery) often tend to co-exist with negative affect (e.g., feeling angry that understaffing may jeopardize other patients' recovery). Although these specific profiles appear to be unique to the nursing occupation, it is important to note that large profiles (corresponding to roughly half of the sample) characterized by mixed emotions were also previously identified in the sport area (Martinent et al., 2013; Martinent & Nicolas, 2017a). In the work area, these "mixed emotions" profiles provide the first person-centered evidence to confirm that some categories of employees can simultaneously experience both positive and negative emotions about their work (Larsen et al., 2017). Interestingly, in both profiles, these emotional states were seen as interfering with performance. More specifically, in both these profiles, which were the only ones characterized by above average levels of positive affect, it was the positive affective states (rather than the negative ones) that were seen as interfering with performance. This surprising result could be explained by the fact that such inconsistent affective experiences (i.e., mixed emotions), by creating ambivalence and confusion, could end up interfering with performance. Our results suggest that it is the experience of positive affective states, when they occur on top of negative affective states, that creates this type of ambivalence and confusion. Clearly, future research is needed to better unpack the mechanisms at play in these profiles.

Finally, our results show that these distinct configurations of affective states seemed to be experienced in a relatively stable manner over time. On the one hand, within-sample stability was pretty strong in the present study and observed differences in within profile means and variances were small enough to be negligible, suggesting that they might simply reflect the lower sample size available at Time 2. On the other hand, within-person stability was also quite high. Indeed, results showed that membership into most of the identified profiles was very stable over time (i.e., stability > 85%). In fact, membership into only one profile appeared to be slightly less stable over time (i.e., *Low Negative Affect Facilitators* profile, with a stability of 59.8%). This result supports those previously reported by Sandrin et al. (2020), showing that a profile in which negative affect is seen as favoring performance is harder to maintain over time than the other profiles. However, it should be noted that, in the present study, this profile was far more stable than in Sandrin et al.'s (2020) study (stability of 9.3%). This could be due to the fact that, in Sandrin et al.'s (2020) study, close to half of the participants (40.1%) were volunteer firefighters. In France, where Sandrin et al.'s (2020) study was realized, these volunteers typically have a full-time job outside of firefighting and only work for the fire station for a few hours each week, on their free time. The volatility of their professional reality could thus explain their higher likelihood of transitioning to other profiles, whereas most of the nurses surveyed in our study held a full-time permanent nursing position, explaining the higher stability of their work-related affective experiences. More generally, our results support the idea that the profiles reflect a stable phenomenon that can be relied upon to guide interventions (Meyer & Morin, 2016). However, additional research is needed to identify the work context components (fire station versus nursing; male-dominated versus female-dominated) at play in influencing employees' ability to maintain, over time, a profile characterized by negative affect seen as favoring performance.

***Job Demands, Job Resources, and Nurses' Affect Profiles***

Addressing a call for increased research attention on the role played by job demands and resources involved in driving employees' affective states and performance at work (Bakker & Demerouti, 2017), we sought to document the role played by various work characteristics, likely to offer useful levers of intervention, in the prediction of nurses' membership into the various profiles identified in this study. Turning first our attention to job demands, we found that exposure to higher levels of emotional load and physical demands both predicted membership into the least desirable (from an outcome perspective, as outlined in the next section) *High Negative Affect Incapacitators* profile. This result confirms prior results showing that work-related stressors have detrimental implications for nurses' affective well-being (Dewey & Allwood, 2022; Schulz et al., 2021). More precisely, these types of job demands are likely to trigger negative emotional arousal (Hakanen et al., 2017; Virtanen et al., 2021), leading to reduced levels of performance (Bakker & Heuven, 2006; Ruitenburg et al., 2013). Although our research was conducted prior to the COVID-19 pandemic, this result should be considered with even more attention during health crises where extraordinary demands are placed upon nurses (Barello et al., 2020).

For instance, research has shown that the detrimental implication of job demands for nurses' affective well-being do not fade away after a few days, but unfold over longer periods of time (Schulz et al., 2021), and may even generate extreme types of emotional distress (i.e., emotional exhaustion, secondary traumatic stress; Dewey & Allwood, 2022). In this context, this result should encourage health organizations to provide nurses with working conditions allowing them to better attend to the inevitable demands of their job. Indeed, although emotional load and physical demands are inherent to nurses' jobs and hard to reduce effectively, organizations could identify ways to reduce other types of hindering demands likely to interfere with nurses' ability to efficiently meet the requirements of their jobs (e.g., red tape; Riedl & Thomas, 2019). Likewise, more frequent rest periods, even short ones, could be better planned to allow nurses to recover more efficiently from their exposure to unavoidable demands (Wendsche et al., 2017).

Organizations could also consider implementing Rational Emotional Behavior Coaching (REBC; Jones et al., 2021; Wood et al., 2021). This cognitive-behavioral intervention is based on the premises that individuals hold rational and irrational beliefs about undesirable events (e.g., job demands), and that these beliefs determine the functionality (or directionality) of their emotional functioning. While irrational beliefs about job demands can lead to negative emotions (e.g., anger, anxiety) that obstruct goal achievement, rational beliefs can lead to other types of negative emotions (e.g., concern, sadness) that facilitate goal achievement. REBC thus acknowledges that resilience in the face of adversity does involve negatively valenced affective states and seeks to train employees to experience more facilitative negative emotions, rather than obstructive ones. By tackling irrational beliefs and encouraging employees to respond to adversity through facilitative, rather than obstructive, negative emotions, REBC has proven effective in shifting employees' beliefs about undesirable aspects of their jobs (e.g., job demands) and in helping them overcome adversity in the workplace among emotionally demanding occupations (i.e., firefighters, Wood et al., 2021; police officers, Jones et al., 2021).

Furthermore, higher levels of emotional load predicted a higher likelihood of membership into the *Mixed Emotions Incapacitators* profile, while higher levels of physical demands predicted a lower likelihood of membership into this same profile. This profile was characterized by the presence of above average levels of both positive and negative affect, both with a detrimental effect on performance. This profile was thus similar to the *High Negative Affect Incapacitators* profile, but also implied in the experience of higher levels of positive affect. This set of results thus suggests that while emotional load may be more likely to lead to the experience of mixed emotions, physical load seems to prevent the experience of mixed emotions. Supporting this assertion was the observation that emotional load also increased the likelihood of membership into the *Mixed Emotions Incapacitators* profile relative to the *Normative* one, whereas physical demands predicted the opposite association. These observations might result from the fact that nurses' emotional load tends to be inextricably related to the interpersonal component of their job (i.e., helping others) and, as a result, may entail the experience of positive emotions. This interpretation is consistent with the idea that, among nurses, emotional demands may act more as a challenge than as a hindrance type of demand (Bakker & Sanz Vergel, 2013). Another contrasting pattern of association was found for emotional load and physical demands: While the former was associated with a higher likelihood of membership into the *Mixed Emotions Incapacitators* profile, relative to the *Intense Mixed Emotions Incapacitators* profile, the opposite was true for the latter. This result shows that, when they trigger mixed emotions, physical demands tend to trigger intense ones. This could be explained by the fact that physical demands maintain workers in a constant state of arousal (Garde et al., 2002), which is likely to cause agitation and to come with intense affective experiences.

In terms of job resources, task identity and interdependence both predicted a higher likelihood of membership into the *Low Negative Affect Facilitators* profile. Interestingly, this profile was not only the sole profile in which affective states were seen as having a facilitative effect on performance, it was also the profile in which the lowest levels of negative affect were observed. This result thus suggests that these motivational job characteristics might have the ability to limit the experience of negative affect, and to help nurses perceive their work-related affective experiences in a way that supports their performance (Humphrey et al., 2007). Moreover, higher levels of task identity and task variety were associated with a reduced likelihood of membership into the *High Negative Affect Incapacitators* profile. These task characteristics thus also have the power to protect nurses from experiencing the most detrimental (from an outcome perspective) affective experiences at work. When considered together, these results are consistent with prior results supporting the benefits of job resources in relation to nurses' affective states (Lehmann et al., 2020). These results also generally support the beneficial role of job resources emphasized by the JD-R theory (Bakker & Demerouti, 2017) and encourage managers to nurture and support job resources within healthcare organizations. Workshops could be organized for nurses to help management identify realistic ways to reinforce the motivational characteristics of their job. Nurses could also benefit from job crafting interventions, in order to train them on the strategies they may use to increase the structural and social resources of their job (Huyghebaert-Zouaghi et al., 2020).

Such interventions should be implemented while keeping in mind that some job resources can also trigger negative affect, together with positive affect. Indeed, task identity also increased (though to a lesser extent) the likelihood of membership into the mixed emotions profiles (i.e., *Intense Mixed Emotions Incapacitators* and *Mixed Emotions Incapacitators*), while task variety reduced the likelihood of membership into the *Mixed Emotions Incapacitators* profile. This result indicates that distinct job resources can have differentiated effects and that some job resources could generate mixed emotions. These contrasted results contradict the assumption that job resources are only beneficial (Bakker & Demerouti, 2017) and suggest that there could be a dark side to job resources. More research is clearly needed to understand the conditions under which some job resources (e.g., task identity) could be involved in the development of negative emotions.

### *Physical Health Implications of Nurses' Affect Profiles*

Given the prevalence of somatic symptoms and musculoskeletal disorders in the nursing occupation (Barello et al., 2020; Ribeiro et al., 2017), this study sought to address a call for research seeking to uncover the associations between affective states and physical health (Bakker & Demerouti, 2017), by considering the associations between profile membership and these two health outcomes. Although few statistically significant differences were observed between profiles in relation to these outcomes, our results were quite clear, consistent across outcomes, and aligned with our expectations, in showing that the most severe health problems seemed to be associated with the *High Negative Affect Incapacitators* profile. These results are consistent with affective events theory (Weiss & Cropanzano, 1996), suggesting that the accumulation of negative emotional experiences (i.e., high levels of negative affect seen as interfering with performance) could be involved in the emergence of physical complaints, due to the nature of the physiological systems involved in these emotional experiences of negative affect (e.g., Fredrickson et al., 2000; Steptoe et al., 2005).

However, when considering these results, it is important to keep in mind that this *High Negative Affect Incapacitators* profile was not the one where the highest levels of negative affect were observed, nor was it the one in which the lowest levels of affect direction (i.e., detrimental effect) were noted. Indeed, higher levels on both of these dimensions were observed in the *Intense Mixed Emotions Incapacitators* profile, which did not differ from the other profiles in terms of health-related outcomes. This result highlights the protective role played by the joint experience of positive affect, which might have helped to prevent the emergence of health-related difficulties (van Steenberger et al., 2021), possibly due the distinct set of physiological systems involved in the experience of positive affect (e.g., Fredrickson et al., 2000; Steptoe et al., 2005). These results thus suggest that experiencing low levels of positive affect (which were the lowest in the *High Negative Affect Incapacitators*) might possibly be more harmful for nurses than the experience of more intense negative affective states. Clearly, these results highlight the need for more research on the affect-health connections to better understand the physiological mechanisms underlying these associations.

## Limitations and Future Research Perspectives

Although this research offered some important theoretical and practical contributions, it still presents limitations. First, we relied on a convenience sample of French nurses, and less than 40% of them completed the Time 2 questionnaire. As a result, it is currently unknown whether our results would generalize to other cultural or occupational groups, and this generalizability is further limited by attrition. It would be important for future research to document the generalizability of the present results among distinct occupational groups, types of organizations, and countries, and to adopt more engaging recruitment procedures seeking to maximize retention over time. Second, we relied on self-report measures. Although shared method variance is unlikely to play a role in multivariate person-centered analyses (Meyer & Morin, 2016), it remains possible that our results might have been influenced by self-report and social desirability biases. It would thus be important for future research to expand upon our results by relying on objective or informant-reported measures (e.g., medical assessment of musculoskeletal disorders). Third, this study was conducted over the course of three months. Although this time span was specifically selected as being the most suitable for the present study, it remains that longitudinal designs conducted over longer (e.g., a year; Wright & Shaw, 1999) or shorter (e.g., a daily diary study; Daniels et al., 2014) periods could yield different conclusions, allowing researchers to better understand long-term tendencies or short-term dynamics. Fourth, we only examined work-related antecedents of nurses' affective states. Yet, longer-term, and more stable measures of trait affectivity (i.e., a dispositional affective tendency; Watson et al., 1988) are also important for performance (Shockley et al., 2012). Dispositional characteristics (e.g., personality, emotional intelligence) are also likely to play a role in influencing work-related affect intensity and direction. For instance, whereas some individuals mainly use emotion-focused (i.e., seeking to regulate their emotional responses) or avoidant (i.e., denying or ignoring negative events) coping strategies and tend to see their affective states as interfering with their performance (Delegach & Katz-Navon, 2021), other individuals rather rely on problem-focused coping strategies (i.e., seeking to resolve the issue) and tend to appraise their affective states as challenges likely to facilitate goal attainment and well-being. Future research may thus benefit from analyzing how contextual and dispositional characteristics may jointly influence nurses' emotional experiences at the trait and state level, as well as the role played by these experiences for a broader range of outcomes encompassing personal and professional well-being.

## Conclusion

In a context where research on nurses' work-related affect is scarce, we documented the nature of nurses' affective states, while considering the functionality of these states, and we showed that nurses' affective experiences differ from other occupations (e.g., fire station employees; Sandrin et al., 2020). By offering a first examination of the health-related consequences of affect profiles, we contributed to identify which affective experiences are most beneficial for nurses over time. By providing a first investigation of job characteristics as predictors of affect profiles at work, we identified some key levers that may guide interventions aiming to promote more desirable affective experiences (Meyer & Morin, 2016). Prior research has also demonstrated that short interventions could successfully change individuals' mindsets, helping them to perceive their affective experiences in a more facilitating and less interfering manner, and to experience reduced levels of undesirable forms of physiological arousal (Crum et al., 2017). Likewise, interventions also exist to help employees experience more desirable (less negative and more positive) affective states at work (e.g., Zhao et al., 2019). Naturally, such interventions would greatly benefit from simultaneously changing the environmental conditions (e.g., job demands) at play in triggering less desirable affective states among nurses.

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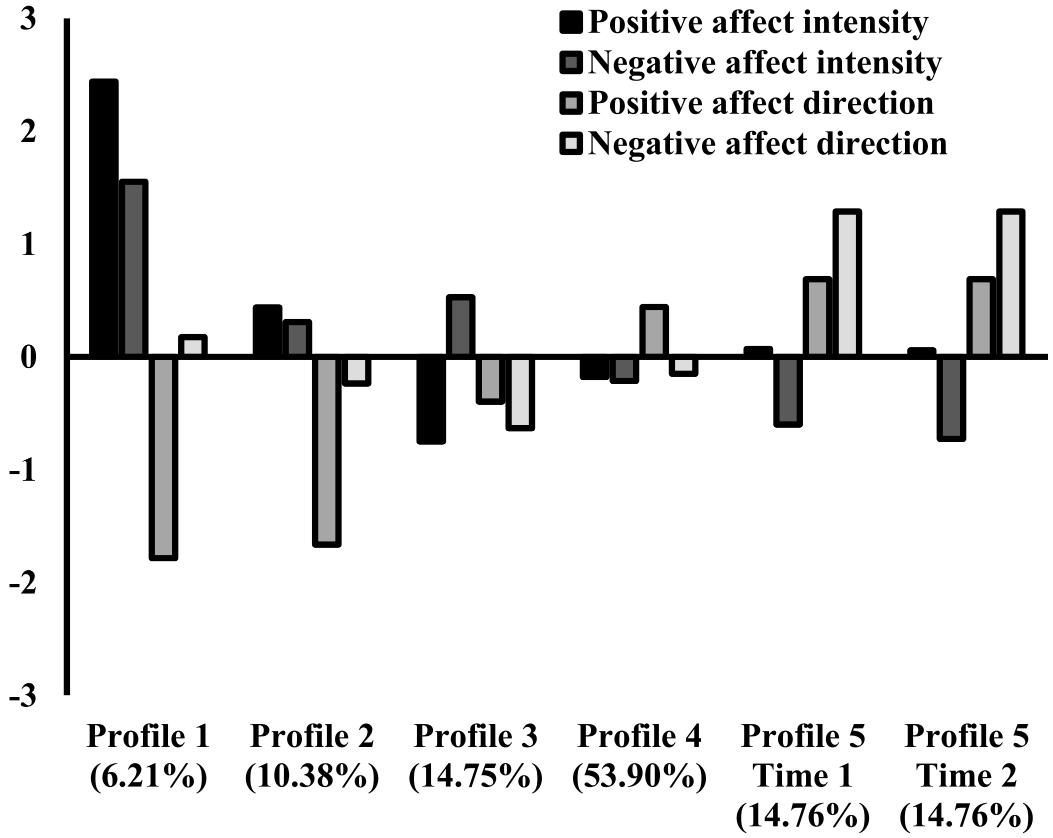


**Figure 1**

*Final Five-Profile Solution.*

*Note*. Profile indicators are factor scores estimated in standardized units ($M = 0$; $SD = 1$); Profile 1: *Intense Mixed Emotions Incapacitators*; Profile 2: *Mixed Emotions Incapacitators*; Profile 3: *High Negative Affect Incapacitators*; Profile 4: *Normative*; Profile 5: *Low Negative Affect Facilitators*.

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

| Model | LL | #fp | Scaling | AIC | CAIC | BIC | ABIC | Entropy | aLMR | BLRT |
|---|---|---|---|---|---|---|---|---|---|---|
| Time 1 | | | | | | | | | | |
| 1 Profile | -6073.686 | 8 | 1.290 | 12163.371 | 12211.703 | 12203.703 | 12178.292 | Na | Na | Na |
| 2 Profiles | -5474.011 | 13 | 1.281 | 10974.021 | 11052.553 | 11039.559 | 10998.267 | .974 | < .001 | < .001 |
| 3 Profiles | -5201.624 | 18 | 1.365 | 10439.247 | 10547.993 | 10529.993 | 10472.819 | .941 | < .001 | < .001 |
| 4 Profiles | -5018.484 | 23 | 1.255 | 10082.968 | 10221.920 | 10198.920 | 10125.865 | .892 | < .001 | < .001 |
| 5 Profiles | -4883.680 | 28 | 1.736 | 9823.360 | 9992.519 | 9964.519 | 9875.583 | .879 | .308 | < .001 |
| 6 Profiles | -4777.411 | 33 | 1.266 | 9620.822 | 9820.371 | 9787.189 | 9682.371 | .886 | < .001 | < .001 |
| 7 Profiles | -4719.888 | 38 | 1.317 | 9515.776 | 9745.350 | 9707.350 | 9586.650 | .859 | .081 | < .001 |
| 8 Profiles | -4648.692 | 43 | 1.397 | 9383.383 | 9643.164 | 9600.164 | 9463.583 | .872 | .154 | < .001 |
| Time 2 | | | | | | | | | | |
| 1 Profile | -5164.151 | 8 | 1.421 | 10344.301 | 10392.633 | 10384.633 | 10359.222 | Na | Na | Na |
| 2 Profiles | -4479.327 | 13 | 1.524 | 8984.653 | 9063.192 | 9050.192 | 9008.900 | .964 | < .001 | < .001 |
| 3 Profiles | -4220.140 | 18 | 1.809 | 8476.281 | 8585.026 | 8567.026 | 8509.852 | .903 | .057 | < .001 |
| 4 Profiles | -4015.172 | 23 | 1.430 | 8076.343 | 8215.296 | 8192.296 | 8119.241 | .893 | < .001 | < .001 |
| 5 Profiles | -3884.865 | 28 | 1.488 | 7825.731 | 79994.890 | 7966.890 | 7877.954 | .877 | .009 | < .001 |
| 6 Profiles | -3774.186 | 33 | 1.357 | 7614.371 | 7813.738 | 7780.738 | 7675.920 | .920 | < .001 | < .001 |
| 7 Profiles | -3700.461 | 38 | 1.359 | 7476.922 | 7706.496 | 7668.496 | 7547.797 | .918 | .020 | < .001 |
| 8 Profiles | -3616.910 | 43 | 1.595 | 7319.819 | 7579.600 | 7536.600 | 7400.019 | .871 | .294 | < .001 |

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

**Table 2**
*Longitudinal Latent Profile and Latent Transition Analyses*

| Model | LL | fp | Sc | AIC | CAIC | BIC | ABIC | Entropy |
|---|---|---|---|---|---|---|---|---|
| *Longitudinal Tests of Similarity* | | | | | | | | |
| Configural | -8768.545 | 56 | 1.6120 | 17649.090 | 17987.409 | 17931.409 | 17753.536 | .878 |
| Structural | -8856.001 | 36 | 1.9667 | 17784.002 | 18001.493 | 17965.493 | 17851.146 | .875 |
| Partial Structural | -8831.022 | 38 | 1.9026 | 17738.044 | 17967.618 | 17929.618 | 17808.918 | .875 |
| Dispersion | -8925.298 | 34 | 2.1149 | 17918.595 | 18124.003 | 18090.003 | 17982.009 | .888 |
| Partial Dispersion | -8792.909 | 38 | 1.6470 | 17661.817 | 17891.391 | 17853.391 | 17732.692 | .850 |
| Distributional | -8803.169 | 34 | 1.8131 | 17674.339 | 17879.747 | 17845.747 | 17737.752 | .846 |
| *Latent Transition Analysis* | -2133.162 | 24 | 0.3334 | 4314.325 | 4459.319 | 4435.319 | 4359.087 | .900 |
| *Predictors* | | | | | | | | |
| Profile-Specific Free Relations with Predictors (Step 1) | -1964.623 | 164 | 0.3609 | 4257.245 | 5248.037 | 5084.037 | 4563.123 | .911 |
| Free Relations with Predictors (Step 2) | -1989.993 | 64 | 0.7775 | 4107.987 | 4494.637 | 4430.637 | 4227.354 | .901 |
| Predictive Similarity (Step 3) | -1999.907 | 44 | 0.6806 | 4087.814 | 4353.637 | 4309.637 | 4169.879 | .903 |
| *Outcomes* | | | | | | | | |
| Free Relations with Outcomes (Step 1) | -6700.226 | 48 | 0.9249 | 13496.452 | 13786.440 | 13738.440 | 13585.977 | .905 |
| Explanatory Similarity (Step 2) | -6708.568 | 38 | 1.1153 | 13493.136 | 13722.710 | 13684.710 | 13564.010 | .904 |

*Note*. LL: Loglikelihood; fp: Free parameters; Sc: Correction factor for robust maximum likelihood estimation; AIC: Akaïke information criteria; BIC: Bayesian information criteria; CAIC: Constant AIC; ABIC: Sample size adjusted BIC; BLRT: Bootstrap likelihood ratio test; aLMR: Adjusted Lo-Mendel-Rubin likelihood ratio test.

**Table 3**
*Transitions Probabilities*

| | Profile 1 | Profile 2 | Profile 3 | Profile 4 | Profile 5 |
|---|---|---|---|---|---|
| *Time 1* | | | | | |
| Profile 1 | .852 | .148 | .000 | .000 | .000 |
| Profile 2 | .000 | 1.00 | .000 | .000 | .000 |
| Profile 3 | .000 | .000 | 1.00 | .000 | .000 |
| Profile 4 | .000 | .000 | .000 | .964 | .036 |
| Profile 5 | .000 | .000 | .016 | .386 | .598 |

*Note.* Profile 1: *Intense Mixed Emotions Incapacitators*; Profile 2: *Mixed Emotions Incapacitators*; Profile 3: *High Negative Affect Incapacitators*; Profile 4: Normative; Profile 5: *Low Negative Affect Facilitators*.

**Table 4**

*Relations between the Predictors and Profile Membership*

| | Profile 1 vs. Profile 5 | | Profile 2 vs. Profile 5 | | Profile 3 vs. Profile 5 | | Profile 4 vs. Profile 5 | | Profile 1 vs. Profile 4 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. (SE) | OR | Coef. (SE) | OR | Coef. (SE) | OR | Coef. (SE) | OR | Coef. (SE) | OR |
| Task variety | .018 (.192) | 1.018 | -.289 (.164) | .749 | -. 293(.153) | .746 | .090 (.118) | 1.094 | -.072 (.178) | .931 |
| Task identity | -.310 (.186) | .733 | -.540 (.146)** | .583 | -. 966 (.138)** | .381 | -.332(.113)** | .718 | .022 (.165) | 1.022 |
| Interdependence | -.227 (.213) | .797 | -.024 (.203) | .977 | -.110 (.190) | .896 | -.282 (.129)* | .754 | .055 (.193) | 1.056 |
| Physical demands | -.891 (.144)** | .410 | -.616 (.133)** | .540 | .175 (.152) | 1.191 | .237 (.112)* | 1.268 | -.128 (.128)** | .324 |
| Emotional load | .240 (.200) | 1.271 | .647 (.148)** | 1.910 | .587 (.158)** | 1.798 | .263 (.093)** | 1.300 | -.023 (.190) | .977 |
| | Profile 2 vs. Profile 4 | | Profile 3 vs. Profile 4 | | Profile 1 vs. Profile 3 | | Profile 2 vs. Profile 3 | | Profile 1 vs. Profile 2 | |
| | Coef. (SE) | OR | Coef. (SE) | OR | Coef. (SE) | OR | Coef. (SE) | OR | Coef. (SE) | OR |
| Task variety | -.378 (.145)** | .685 | -.383 (.132)** | .682 | .311 (.198) | 1.365 | .005 (.166) | 1.005 | .306 (.192) | 1.358 |
| Task identity | -.208 (.117) | .812 | -.634 (.105)** | .531 | .655 (.179)** | 1.926 | .426 (.135)** | 1.531 | .230 (.173) | 1.258 |
| Interdependence | .259 (.181) | 1.295 | .172 (.164) | 1.188 | -.117 (.235) | .889 | .086 (.218) | 1.090 | -.204 (.225) | .816 |
| Physical demands | -.853 (.113)** | .426 | -.062 (.135) | .940 | -1.066 (.162)** | .344 | -.791 (.149)** | 0.453 | -.275 (.132)* | .759 |
| Emotional load | .385 (.130)** | 1.469 | .324 (.144)* | 1.382 | -.347 (.226) | .707 | .061 (.173) | 1.063 | -.408 (.200)* | .665 |

*Note*. * $p < .05$; ** $p < .01$; All predictors are factor scores estimated in standardized units ($M = 0$; $SD = 1$); SE: Standard error of the coefficient; OR: Odds ratio; the coefficients and OR reflect the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile; Profile 1: *Intense Mixed Emotions Incapacitators*; Profile 2: *Mixed Emotions Incapacitators*; Profile 3: *High Negative Affect Incapacitators*; Profile 4: Normative; Profile 5: *Low Negative Affect Facilitators*.

**Table 5**

*Relations between Profile Membership and the Outcomes*

| | Profile 1<br>M [CI] | Profile 2<br>M [CI] | Profile 3<br>M [CI] | Profile 4<br>M [CI] | Profile 5<br>M [CI] | Summary of Significant Differences |
|---|---|---|---|---|---|---|
| Somatic symptoms | -.188<br>[-.339; -.037] | -.099<br>[-.253; .055] | .894<br>[.797; .991] | -.180<br>[-.284; -.076] | -.316<br>[-.543; -.088] | 3 > 1 = 2 = 4 = 5 |
| Musculoskeletal disorders | -.136<br>[-.255; -.016] | -.077<br>[-.226; .072] | .834<br>[.745; .923] | -.101<br>[-.197; -.005] | -.056<br>[-.264; .151] | 3 > 1 = 2 = 4 = 5 |

*Note*. All outcomes are factor scores estimated in standardized units ($M$ = 0; $SD$ = 1); M: Mean; CI: 95% confidence interval; Profile 1: *Intense Mixed Emotions Incapacitators*; Profile 2: *Mixed Emotions Incapacitators*; Profile 3: *High Negative Affect Incapacitators*; Profile 4: Normative; Profile 5: *Low Negative Affect Facilitators*.

**Online Supplemental Materials for:**

**Nature, Predictors, and Outcomes of Nurses' Affect Profiles: A Longitudinal Examination**

## Preliminary Measurement Models

### Model Estimation and Specification

Preliminary measurement models were estimated using Mplus 8 (Muthén & Muthén, 2017) to verify the psychometric properties of all of our measures and their measurement invariance over time. For the affect and predictor measures, we relied on the Maximum Likelihood robust (MLR) estimator, which is robust to non-normality. For the outcome measures, we relied on the robust mean and variance adjusted weight least square estimator (WLSMV), which has been shown to outperform MLR estimation for items rated using an ordinal (somatic symptoms) or binary (musculoskeletal disorders) scale of measurement (Finney & DiStefano, 2013). Item-level missing data remained low for participants who participated at each measurement occasion (i.e., 0 to 7.87% at Time 1; 0 to 7.22% at Time 2). The complexity of these longitudinal measurement models (including multiple items, factors, time points, and an exploratory structural equation modeling component for the profile indicators) made it necessary to conduct the analyses separately for the affect measure, for the multi-item predictors measures (i.e., task variety, task identity, received interdependence, physical demands, emotional load), and for the multi-item outcomes measures (i.e., somatic symptoms, musculoskeletal disorders). Attempts to combine these measurement models systematically resulted in nonconverging solutions.

For the affect measure, we relied on an exploratory structural equation modeling (ESEM) measurement model including four correlated factors (positive affect intensity, positive affect direction, negative affect intensity, and negative affect direction). These factors were specified using a confirmatory oblique target rotation procedure (Asparouhov & Muthén, 2009; Browne, 2001), which made it possible to estimate all cross-loadings while targeting them to be as close to 0 as possible. Statistical evidence showed that ESEM provides more exact estimates of factor correlations when cross-loadings are present in the population model while remaining unbiased otherwise (Asparouhov et al., 2015), and has thus been repeatedly recommended for measurement models involving conceptually related constructs (e.g., Morin et al., 2017, 2020). For the predictors (5 factors) and outcomes (i.e., 2 factors) for which it did not appear relevant to incorporate cross-loaigns between items referring to completely distinct constructs (e.g., Morin et al., 2017), we relied on a more classical confirmatory factor analysis (CFA) specification. In these models, all factors were solely defined by their *a priori* indicators.

After having verified the psychometric properties of these measurement models at each separate time points, longitudinal models were estimated across the two-time waves to verify the measurement invariance of these models. These longitudinal models thus incorporated eight correlated factors (i.e., 4 factors x 2 times) for the affect measure, ten correlated factors for the predictor measures (i.e., 5 factors x 2 times) and four correlated factors for the outcome measures (i.e., 2 factors x 2 times). In these models, correlated uniquenesses were included *a priori* between matching items used across time waves to avoid converging on inflated estimates of longitudinal stability (e.g., Marsh, 2007).

The measurement invariance of these models was systematically tested over time according to the following sequence (Millsap, 2011): (i) configural (same model); (ii) weak (same loadings); (iii) strong (same intercepts or thresholds for WLSMV estimation); (iv) strict (same uniquenesses); (v) latent variances and covariances (same latent variance-covariance matrix); and (vi) latent means (same latent means). It should be noted that for the outcome measurement models, it is not possible to separately test for the invariance of the factors loadings and response thresholds with binary items. For this reason, step 2 (weak invariance) only involved placing equality constraints on the factor loadings of the somatic symptoms indicators, whereas step 3 (strong invariance) involved placing equality constraints on the loadings and response thresholds of the musculoskeletal disorders indicators and on the response thresholds of the somatic symptoms indicators.

Model fit was assessed using sample-size independent fit indices to account for the oversensitivity (to sample size and minor misspecifications) of the chi-square ($\chi^2$) and of chi-square difference tests (e.g., Hu & Bentler, 1999; Marsh et al., 2005). More precisely, we considered values over .90 on the comparative fit index (CFI) and on the Tucker-Lewis index (TLI) to support adequate fit, and values over .95 to support excellent fit. For the root mean square error of approximation (RMSEA), matching values were respectively smaller than .08 and .06. For tests of invariance, we considered changes ($\Delta$) in CFI/TLI of .010 or less and $\Delta$RMSEA of .015 or less to support the most invariant model.

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**Table S1**

*Preliminary Measurement Models: Goodness-of-Fit Statistics (Affects)*

| Description | $\chi^2$ (*df*) | CFI | TLI | RMSEA | 90% CI | CM | $\Delta\chi^2$ (*df*) | ΔCFI | ΔTLI | ΔRMSEA |
|---|---|---|---|---|---|---|---|---|---|---|
| Time 1 | 278.137 (54)* | .962 | .916 | .060 | [.053; .067] | | | | | |
| Time 2 | 131.082 (54)* | .962 | .916 | .061 | [.048; .074] | | | | | |
| Longitudinal M1. Configural invariance | 664.528 (332)* | .964 | .946 | .030 | [.026; .033] | - | - | - | - | - |
| Longitudinal M2. Weak invariance | 735.238 (380)* | .961 | .950 | .029 | [.025; .032] | M1 | 71.293 (48) | -.003 | +.004 | -.001 |
| Longitudinal M3. Strong invariance | 758.476 (392)* | .960 | .950 | .029 | [.026; .032] | M2 | 23.238 (12) | -.001 | -.001 | .000 |
| Longitudinal M4. Strict invariance | 807.284 (408)* | .957 | .947 | .029 | [.026; .032] | M3 | 43.269 (16)* | -.003 | -.003 | .000 |
| Longitudinal M5. Var-Cov invariance | 822.072 (418)* | .956 | .948 | .029 | [.026; .032] | M4 | 15.475 (10) | -.001 | +.001 | .000 |
| Longitudinal M6. Latent means invariance | 827.401 (422)* | .956 | .948 | .029 | [.026; .032] | M5 | 5.287 (4) | -.000 | .000 | .000 |

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

**Table S2**

*Standardized Factor Loadings (λ), Uniquenesses (δ), and Correlations for the Affect Measurement Models*

| | ESEM Time 1 | | | | | ESEM Time 2 | | | | | ESEM: Time 1 and 2 Latent Mean Invariance | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Items | PAI λ | NAI λ | PAD λ | NAD λ | δ | PAI λ | NAI λ | PAD λ | NAD λ | δ | PAI λ | NAI λ | PAD λ | NAD λ | δ |
| PAI 1 | .409** | -.297** | .075 | -.010 | .769** | .522** | -.209** | .135* | -.068 | .691** | .506** | -.257** | .108* | -.024 | .756** |
| PAI 2 | .373** | -.167** | .317** | .058 | .761** | .499** | -.232** | .241* | -.073 | .664** | . 441** | -.179** | .328** | .014 | .741** |
| PAI 3 | .636** | .239** | .050 | .044 | .526** | .607** | .233** | .052 | .061 | .574** | . 588** | .291** | .130** | .031 | .522** |
| PAI 4 | .772** | .154* | .252** | -.012 | .422** | .703** | .118* | .204* | .035 | .493 ** | . 714** | .199** | .317** | -.014 | .443** |
| ω | .659 | | | | | .692 | | | | | .672 | | | | |
| NAI 1 | .348** | .413** | -.433** | .009 | .339** | .268** | .723** | -.235** | .021 | .381** | . 395** | .528** | -.320** | .001 | .338** |
| NAI 2 | .464** | .320** | -.428** | .045* | .228** | .407** | .482** | -.371** | .011 | .258** | . 395** | .402** | -.348** | .035* | .222** |
| NAI 3 | -.215** | .569** | .180** | -.072 | .760** | -.328** | .710** | .267** | -.079* | .778** | -.403** | .638** | .241** | -.092* | .766** |
| NAI 4 | -.214** | .586** | .266** | -.030 | .423** | -.304** | .526** | .235** | -.119* | .547** | -. 375** | .578** | .292** | -.076* | .461** |
| ω | | .670 | | | | | .752 | | | | | .720 | | | |
| PAD 1 | -.003 | -.125** | .780** | -.006 | .352** | .055 | -.107* | .750 ** | .026 | .235** | -. 015 | -.133** | .754** | -.003 | .321** |
| PAD 2 | -.017 | -.109* | .833** | .064** | .320** | .076* | -.105* | .832** | .001 | .314** | -. 018 | -.125** | .817** | .038* | .307** |
| PAD 3 | .214** | -.126* | .147** | .317** | .601** | .294** | -.012 | .185* | .262** | .365 ** | . 261** | -.062* | .166** | .305** | .521** |
| PAD 4 | .485** | .042 | .701** | .081** | .575** | .413** | .021 | .555** | .116* | .574** | . 416** | .042 | .705** | .082** | .585** |
| ω | | | .766 | | | | | .783 | | | | | .775 | | |
| NAD1 | .130** | -.080* | -.165** | .620** | .521** | .093* | -.054 | -.109* | .713** | .434** | . 160** | -.053* | -.162** | .646** | .502** |
| NAD2 | .054* | .060* | -.150** | .754** | .436** | .047 | .098* | -.038 | .785** | .391** | . 062* | .092** | -.131** | .764** | .420** |
| NAD3 | -.094** | -.042 | -.012 | .818** | .337** | -.107** | -.136** | -.107* | .86** | .224** | -. 066* | -.074* | -.067* | .833** | .309** |
| NAD4 | -.272** | .066 | .439** | .615** | .327** | -.260** | .007 | .409** | .699** | .284** | -. 295** | .019 | .395** | .622** | .308** |
| ω | | | | .829 | | | | | .875 | | | | | .842 | |
| *Factor Correlations* | | 1. | 2. | 3. | 4. | | 1. | 2. | 3. | 4. | | 1. | 2. | 3. | 4. |
| 1. PA | | -- | | | | | -- | | | | | -- | | | |
| 2. NA | | .076 | -- | | | | .004 | -- | | | | .272** | -- | | |
| 3. PAD | | -.268** | -.190** | -- | | | -.144** | -.295** | -- | | | -.271** | -.345** | -- | |
| 4. NAD | | .231** | -.316** | .141** | -- | | .238** | -.235** | .093* | -- | | .214** | -.236** | .184** | -- |

*Note.* * $p < .05$; ** $p < .01$; ESEM: Exploratory structural equation modeling; PA: Positive affect intensity; NA: Negative affect intensity; PAD: Positive affect direction; NAD: Negative affect direction; δ: Standardized item uniqueness; bold: Target factor loadings in the ESEM solutions; ω: Omega coefficient of composite reliability.

**Table S3**

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

| Description | $\chi^2$ (*df*) | CFI | TLI | RMSEA | 90% CI | CM | $\Delta\chi^2$ (*df*) | ΔCFI | ΔTLI | ΔRMSEA |
|---|---|---|---|---|---|---|---|---|---|---|
| Time 1 | 445.658 (125)* | .948 | .937 | .047 | [.043; .052] | | | | | |
| Time 2 | 289.945 (125)* | .936 | .922 | .058 | [.050 ; .067] | | | | | |
| Longitudinal M1. Configural invariance | 1089.495 (531)* | .948 | .938 | .030 | [.028; .033] | - | - | - | - | - |
| Longitudinal M2. Weak invariance | 1097.733 (544)* | .948 | .940 | .030 | [.027; .032] | M1 | 12.008(13) | .000 | +.002 | .000 |
| Longitudinal M3. Strong invariance | 1111.386 (557)* | .948 | .942 | .030 | [.027; .032] | M2 | 11.783(13) | .000 | +.002 | .000 |
| Longitudinal M4. Strict invariance | 1225.081 (575)* | .940 | .934 | .031 | [.029; .034] | M3 | 76.428(18)* | -.008 | -.008 | +.001 |
| Longitudinal M5. Var-Cov invariance | 1248.848 (590)* | .939 | .935 | .031 | [.029; .034] | M4 | 25.092(15) | -.001 | +.001 | .000 |
| Longitudinal M6. Latent means invariance | 1260.569 (595)* | .938 | .934 | .031 | [.029; .034] | M5 | 11.933(5) | -.001 | -.001 | .000 |

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

**Table S4**

*Standardized Factor Loadings (λ), Uniquenesses (δ), and Correlations for the Predictors Measurement Models*

| Items | Time 1 λ | Time 1 δ | Time 2 λ | Time 2 δ | LM Invariance λ | LM Invariance δ |
|---|---|---|---|---|---|---|
| Task variety | | | | | | |
| Item 1 | .756 | .428 | .798 | .363 | .768 | .410 |
| Item 2 | .865 | .251 | .875 | .235 | .869 | .246 |
| Item 3 | .803 | .355 | .747 | .443 | .796 | .366 |
| Item 4 | .821 | .326 | .844 | .288 | .828 | .315 |
| ω | .886 | | .889 | | .888 | |
| Task identity | | | | | | |
| Item 1 | .474 | .775 | .657 | .568 | .519 | .731 |
| Item 2 | .641 | .590 | .746 | .444 | .667 | .556 |
| Item 3 | .843 | .289 | .856 | .268 | .847 | .283 |
| Item 4 | .887 | .214 | .878 | .230 | .881 | .223 |
| ω | .812 | | .867 | | .826 | |
| Interdependence | | | | | | |
| Item 1 | .724 | .475 | .747 | .442 | .727 | .472 |
| Item 2 | .802 | .357 | .809 | .346 | .806 | .350 |
| Item 3 | .600 | .640 | .603 | .637 | .602 | .637 |
| ω | .754 | | .766 | | .758 | |
| Physical demands | | | | | | |
| Item 1 | .713 | .492 | .759 | .423 | .725 | .474 |
| Item 2 | .897 | .196 | .904 | .183 | .898 | .193 |
| Item 3 | .934 | .128 | .960 | .078 | .939 | .118 |
| ω | .888 | | .910 | | .893 | |
| Emotional load | | | | | | |
| Item 1 | .658 | .568 | .725 | .475 | .673 | .547 |
| Item 2 | .358 | .872 | .366 | .866 | .366 | .866 |
| Item 3 | .671 | .550 | .708 | .498 | .681 | .537 |
| Item 4 | .750 | .437 | .845 | .287 | .769 | .409 |
| ω | .710 | | .767 | | .724 | |
| *Factor Correlations (Time 1)* | 1. | 2. | 3. | 4. | 5. | |
| 1.Task variety | -- | | | | | |
| 2. Task identity | .140 | -- | | | | |
| 3. Interdependence | .599 | *.081* | -- | | | |
| 4. Physical demands | .297 | .163 | .411 | -- | | |
| 5. Emotional load | .230 | -.124 | .232 | .111 | -- | |
| *Factor Correlations (Time 2)* | 1. | 2. | 3. | 4. | 5. | |
| 1.Task variety | -- | | | | | |
| 2. Task identity | *.019* | -- | | | | |
| 3. Interdependence | .589 | *.085* | -- | | | |
| 4. Physical demands | .159 | .185 | .259 | -- | | |
| 5. Emotional load | .171 | -.224 | .202 | *.015* | | |
| *Factor Correlations (LM Inv.)* | 1. | 2. | 3. | 4. | 5. | |
| 1.Task variety | -- | | | | | |
| 2. Task identity | .123 | -- | | | | |
| 3. Interdependence | .595 | *.084* | -- | | | |
| 4. Physical demands | .277 | .168 | .383 | -- | | |
| 5. Emotional load | .220 | .220 | .224 | .098 | -- | |

*Note*. LM invariance: Latent mean invariance solution (equal across Time 1 and 2); λ: Factor loading; ω: Omega coefficient of model-based composite reliability; most coefficients are significant at $p < .01$, with the exception of those marked in italic (non-statistically significant).

**Table S5**

*Goodness-of-Fit Statistics for the Estimated Models (Outcomes)*

| Description | $\chi^2$ (*df*) | CFI | TLI | RMSEA | 90% CI | CM | $\Delta\chi^2$ (*df*) | ΔCFI | ΔTLI | ΔRMSEA |
|---|---|---|---|---|---|---|---|---|---|---|
| Time 1 | 151.144 (43)* | .978 | .972 | .047 | [.039; .055] | | | | | |
| Time 2 | 77.178 (43)* | .982 | .977 | .045 | [.028 ; .061] | | | | | |
| Longitudinal M1. Configural invariance | 313.075 (192) | .981 | .977 | .023 | [.019; .028] | - | - | - | - | - |
| Longitudinal M2. Weak invariance | 315.115 (195) | .981 | .977 | .023 | [.018; .028] | M1 | 1.338(3) | .000 | .000 | .000 |
| Longitudinal M3. Strong invariance | 327.548 (211) | .982 | .980 | .022 | [.017; .027] | M2 | 13.090(16) | +.001 | +.003 | -.001 |
| Longitudinal M4. Strict invariance | 333.453 (222) | .982 | .982 | .021 | [.016; .025] | M3 | 9.054(11) | .000 | .002 | -.001 |
| Longitudinal M5. Var-Cov invariance | 338.390 (224) | .982 | .981 | .021 | [.016; .026] | M4 | 4.937(2) | .000 | -.001 | .000 |
| Longitudinal M6. Latent means invariance | 340.343 (226) | .982 | .981 | .021 | [.016; .025] | M5 | 3.143(2) | .000 | .000 | .000 |

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

**Table S6**

*Standardized Factor Loadings (λ), Uniquenesses (δ), and Correlations for the Outcomes Measurement Models*

| Items | Time 1 λ | Time 1 δ | Time 2 λ | Time 2 δ | LM Invariance λ | LM Invariance δ |
|---|---|---|---|---|---|---|
| Somatic symptoms | | | | | | |
| Item 1 | .663 | .560 | .638 | .594 | .680 | .537 |
| Item 2 | .696 | .516 | .713 | .491 | .699 | .511 |
| Item 3 | .697 | .515 | .600 | .640 | .652 | .575 |
| Item 4 | .685 | .531 | .802 | .328 | .725 | .475 |
| ω | .780 | | .787 | | .784 | |
| Musculoskeletal disorders | | | | | | |
| Item 1 | .914 | .165 | .932 | .131 | .922 | .150 |
| Item 2 | .905 | .182 | .943 | .111 | .912 | .168 |
| Item 3 | .676 | .543 | .786 | .382 | .718 | .485 |
| Item 4 | .719 | .484 | .759 | .425 | .730 | .567 |
| Item 5 | .750 | .437 | .805 | .352 | .770 | .408 |
| Item 6 | .701 | .509 | .774 | .400 | .713 | .492 |
| Item 7 | .821 | .326 | .836 | .300 | .829 | .312 |
| ω | .836 | | .872 | | .839 | |
| *Factor Correlations* | 1. | | 1. | | 1. | |
| 1. Somatic symptoms | -- | | -- | | -- | |
| 2. Musculoskeletal disorders | .470 | | .454 | | .460 | |

*Note*. λ: Factor loading; ω: Omega coefficient of model-based composite reliability; all coefficients are significant at $p < .01$.

**Table S7**

*Correlations between all Variables Used in the Present Study*

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Sex T1 | - | | | | | | | | | | | | |
| 2. Age T1 | -.054 | - | | | | | | | | | | | |
| 3. Organizational tenure T1 | -.046 | .551** | - | | | | | | | | | | |
| 4. Positive affect intensity T1[1] | -.038 | .016 | .057 | - | | | | | | | | | |
| 5. Negative affect intensity T1[1] | -.016 | .011 | .149** | .363** | - | | | | | | | | |
| 6. Positive affect direction T1[1] | .069* | -.039 | -.203** | -.333** | -.430** | - | | | | | | | |
| 7. Negative affect direction T1[1] | .019 | .088** | -.041 | .240** | -.264** | .217** | - | | | | | | |
| 8. Task variety T1[1] | .042 | -.024 | -.065* | -.012 | -.053 | .183** | .007 | - | | | | | |
| 9. Task identity T1[1] | -.037 | .082** | -.040 | .092** | -.181** | .193** | .170** | .149** | - | | | | |
| 10. Interdependence T1[1] | .042 | -192* | -.053 | -.071* | -.014 | .176** | .027 | .679** | .101** | - | | | |
| 11. Physical demands T1[1] | .100** | -.029 | -.028 | -.249** | -.121** | .348** | .022 | .316** | .183** | .450** | - | | |
| 12. Emotional load T1[1] | .104** | .021 | -.018 | -.078** | .192** | -.031 | -.154** | .265** | -.153** | .280** | .123** | - | |
| 13. Somatic symptoms T1[1] | .109** | -.012 | -.041 | -.177** | .274** | -.015 | -.201** | .084** | -.175** | .085** | .146** | .308** | - |
| 14. Musculoskeletal disorders T1[1] | .124** | -.058 | .104** | -.150** | .156** | .005 | -.102** | .088 | -.097** | .075* | .253** | .203** | .597** |
| 15. Positive affect intensity T2[1] | -.054 | .014 | .057 | .904** | .327** | -.427** | .143* | -.024 | .063* | -.088** | -.294** | -.047 | -.166** |
| 16. Negative affect intensity T2[1] | -.029 | .021 | .166** | .241** | .843** | -.545** | -.335** | -.071* | -.237** | -.048 | -.161** | .194** | .288** |
| 17. Positive affect direction T2[1] | .064* | -.036 | -.205** | -.425** | -.496** | .978** | .134** | .188** | .185** | .176** | .346** | -.030 | -.016 |
| 18. Negative affect direction T2[1] | .022 | .074* | -.031 | -.197** | -.350** | .187** | .608** | .015 | .176** | .004 | -.022 | -.136** | -.231** |
| 19. Task variety T2[1] | -.003 | -.001 | -.029 | -.032 | -.047 | .153** | .001 | .843** | .077** | .531** | .204** | .199** | .082** |
| 20. Task identity T2[1] | -.042 | .074* | -.041 | .066** | -.158** | .168** | .157** | -.020 | .776** | -.118** | .134** | -.184** | -.120** |
| 21. Interdependence T2[1] | -.004 | -.011 | -.033 | -.124** | -.004 | .137** | -.003 | .504** | -.065* | .752** | .304** | .225** | .115** |
| 22. Physical demands T2[1] | .077** | .020 | -.022 | -.264** | -.116** | .316** | .007 | .221** | .082** | .302** | .911** | .033 | .150** |
| 23. Emotional load T2[1] | .078** | -.033 | .006 | -.074* | .229** | -.116** | -.184** | .198** | -.306** | .208** | .019 | .864** | .301** |
| 24. Somatic symptoms T2[1] | .107** | -.053 | -.041 | -.174** | .264** | -.014 | -.178** | .093** | -.180** | .089** | .150** | .298** | .958** |
| 25. Musculoskeletal disorders T2[1] | .115** | .125** | .081** | -.170** | .164** | .021 | -.104** | .062* | -.111** | .086** | .262** | .197** | .634** |

**Table S7 (Continued)**

*Correlations between all Variables Used in the Present Study*

| Variable | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 14. Musculoskeletal disorders T1[1] | - | | | | | | | | | | | |
| 15. Positive affect intensity T2[1] | -.146** | - | | | | | | | | | | |
| 16. Negative affect intensity T2[1] | .154** | .315** | - | | | | | | | | | |
| 17. Positive affect direction T2[1] | .004 | -.469** | -.565** | - | | | | | | | | |
| 18. Negative affect direction T2[1] | .134** | .207** | -.393** | .199** | - | | | | | | | |
| 19. Task variety T2[1] | .024 | -.008 | -.016 | .169** | .010 | - | | | | | | |
| 20. Task identity T2[1] | -.087** | .047 | -.193** | .173** | .171** | .024 | - | | | | | |
| 21. Interdependence T2[1] | .071* | -.104** | .034 | .155** | -.039 | .652** | -.070* | - | | | | |
| 22. Physical demands T2[1] | .255** | -.305** | -.125** | .323** | -.052 | .225** | .146** | .352** | - | | | |
| 23. Emotional load T2[1] | .181** | -.024 | .293** | -.107** | -.187** | .232** | -.308** | .276** | .024 | - | | |
| 24. Somatic symptoms T2[1] | .580** | -.170** | .309** | -.015 | -.237** | .097** | -.117** | .132** | .176** | .319** | - | |
| 25. Musculoskeletal disorders T2[1] | .927** | -.187** | .179** | .018 | -.164** | .035 | -.081** | .087** | .282** | .188** | .660** | - |

*Note*. * $p < .05$; ** $p < .01$; [1]:These variables are factor scores estimated in standardized units (M = 0; SD = 1); sex was coded 0 for males and 1 for females.

**Table S8**

*Detailed Parameter Estimates from the Final Longitudinal LPA Solution (Distributional Similarity, with Partial Structural and Dispersion Similarity)*

| | Profile 1 *M* [CI] | Profile 2 *M* [CI] | Profile 3 *M* [CI] | Profile 4 Time 1 *M* [CI] | Profile 4 Time 2 *M* [CI] | Profile 5 Time 1 *M* [CI] | Profile 5 Time 2 *M* [CI] |
|---|---|---|---|---|---|---|---|
| Positive Affect Intensity | 2.441 [2.181; 2.701] | .439 [.222; .656] | -.749 [-.882; -.616] | -.178 [-.220; -.136] | -.178 [-.220; -.136] | 070 [.003; .136] | .059 [-.027; .145] |
| Negative Affect Intensity | 1.553 [1.412; 1.694] | .308 [.100; .516] | .530 [.310; .750] | -.212 [-.269; -.154] | -.212 [-.269; -.154] | -.598 [-.667; -.529] | -.725 [-.791; -.658] |
| Positive Affect Direction | -1.784 [-1.894; -1.674] | -1.663 [-1.778; -1.548] | -.396 [-.573; -.218] | .443 [.389; .498] | .443 [.389; .498] | .687 [.642; .732] | .687 [.642; .732] |
| Negative Affect Direction | .174 [.082; .265] | -.237 [-.318; -.157] | -.634 [-.784; -.483] | -.150 [-.212; -.088] | -.150 [-.212; -.088] | 1.289 [1.156; 1.422] | 1.289 [1.156; 1.422] |
| | **Profile 1 V [CI]** | **Profile 2 V [CI]** | **Profile 3 V [CI]** | **Profile 4 Time 1 V [CI]** | **Profile 4 Time 2 V [CI]** | **Profile 5 Time 1 V [CI]** | **Profile 5 Time 2 V [CI]** |
| Positive Affect Intensity | .268 [.239; .296] | .268 [.239; .296] | .268 [.239; .296] | .268 [.239; .296] | .106 [.092; .120] | .268 [.239; .296] | .106 [.092; .120] |
| Negative Affect Intensity | .449 [.407; .490] | .449 [.407; .490] | .449 [.407; .490] | .449 [.407; .490] | .175 [.149; .201] | .449 [.407; .490] | .175 [.149; .201] |
| Positive Affect Direction | .196 [.167; .226] | .196 [.167; .226] | .196 [.167; .226] | .196 [.167; .226] | .122 [.101; .144] | .196 [.167; .226] | .122 [.101; .144] |
| Negative Affect Direction | .309 [.262; .355] | .309 [.262; .355] | .309 [.262; .355] | .309 [.262; .355] | .269 [.189; .350] | .309 [.262; .355] | .269 [.189; .350] |

*Note*. Profile indicators are factor scores estimated in standardized units ($M$ = 0; $SD$ = 1); parameters allowed to vary over time are highlighted in greys; M: Mean; V: Variance; CI: 95% confidence interval; Profile 1: *Intense Mixed Emotions Incapacitators*; Profile 2: *Mixed Emotions Incapacitators*; Profile 3: *High Negative Affect Incapacitators*; Profile 4: Normative; and Profile 5: *Low Negative Affect Facilitators.*

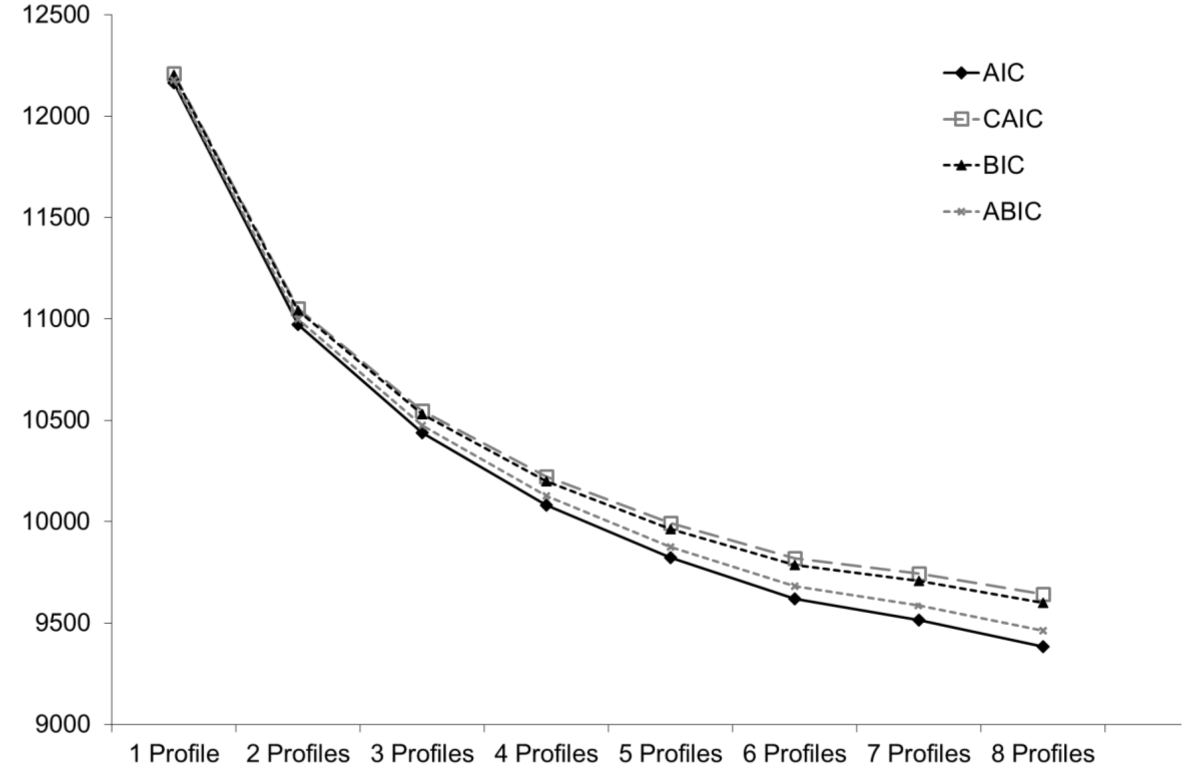


**Figure S1**
*Elbow Plot of the Information Criteria for the Latent Profile Analyses (Time 1)*

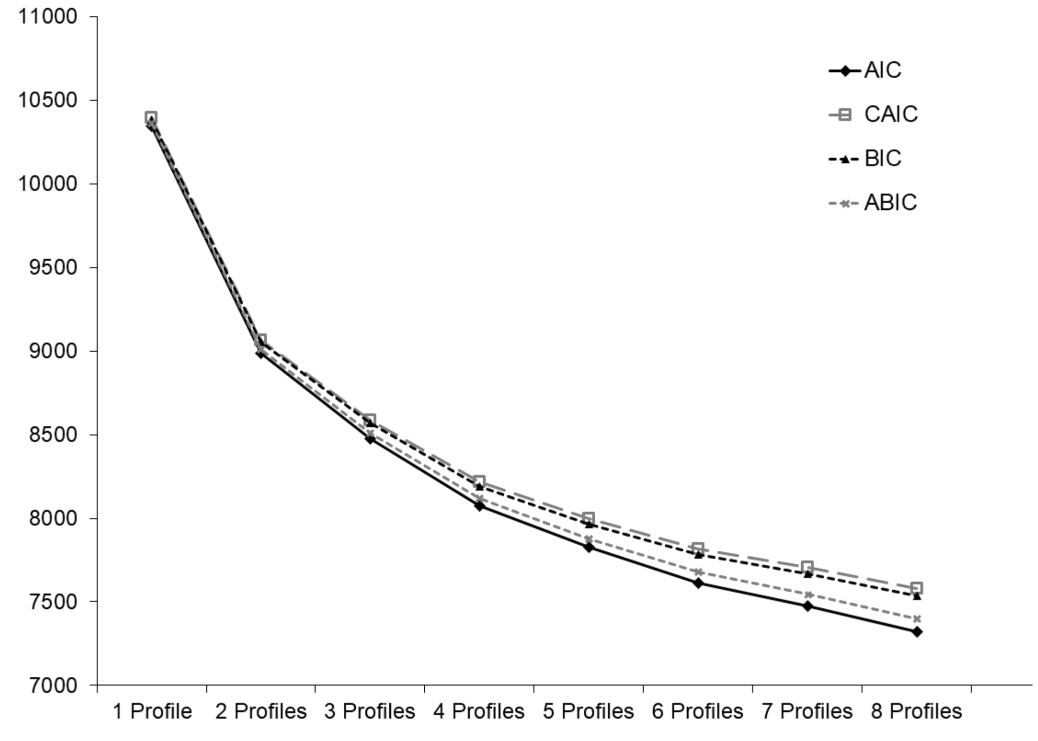


**Figure S2**
*Elbow Plot of the Information Criteria for the Latent Profile Analyses (Time 2)*