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Occupational Well-Being Profiles and Learning Climate as an Organizational Resource: A Latent Transition Analysis

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Abstract
The aim of the present longitudinal study was to profile the occupational well-being (burnout, work engagement) of highly educated employees (n=442) at three measurement points: in 2017 (T1), 2019 (T2), and 2021 (T3). We were interested in whether profile transitions would occur during the follow-up, and if so, whether the three dimensions of perceived learning climate (facilitation, appreciation, and error avoidance) predict these transitions, and hence function as an organizational-level resource that could help highly educated employees to sustain or improve their occupational well-being. We identified three profiles at each measurement point: (1) burnout, lowered engagement; (2) average exhaustion, high engagement; and (3) low burnout, very high engagement. Latent Transition Analysis indicated that employees both maintained their profiles and made transitions during the follow-up. The findings for the second study period (T2-T3) showed a somewhat less favorable development of occupational well-being. Multinomial Logistic Regression Analysis revealed that perceived learning climate predicted the T2-T3 but not T1-T2 transitions. We conclude that employee well-being can simultaneously comprise both positive and negative states. Although the organizational resource perspective gained some support, this tentative evidence also raises the question of whether employees perceive an appreciative learning climate as more stressful than helpful. Overall, the longitudinal relationship of occupational well-being with the dimensions of perceived learning climate warrants further study.

Keywords Sustainable careers · Organizational resources · Occupational well-being · Learning climate · Latent transition analysis · Follow-up study

Abbreviation

COR theory Conservation of resources theory

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LC	Learning climate
EMBA	Executive Master of Business Administration
LPA	Latent Profile Analysis
LTA	Latent Transition Analysis
MLR	Robust Maximum Likelihood Estimator
FIML	Full Information Maximum Likelihood
AIC	Akaike information criterion
BIC	Bayesian information criterion
aBIC	Sample-size adjusted BIC
BLRT	Bootstrap likelihood ratio test
aLMR	Adjusted Lo-Mendell-Rubin likelihood ratio test
VLMR	Vuong-Lo-Mendell-Rubin likelihood ratio test
OR	Odds ratio
CI	Confidence interval (95%)
T1	Time 1 (2017)
T2	Time 2 (2019)
T3	Time 3 (2021)
Profile 1	'Burnout, lowered engagement'
Profile 2	'Average exhaustion, high engagement'
Profile 3	'Low burnout, very high engagement'
EXH	Exhaustion (in tables / figures)
CYN	Cynicism (in tables / figures)
INA	Inadequacy (in tables / figures)
WE	Work engagement (in tables / figures)
FLC	Facilitative learning climate (in tables / figures)
ALC	Appreciative learning climate (in tables / figures)
EALC	Error-avoiding learning climate (in tables / figures)

Introduction

Technological acceleration, acceleration of social change, and acceleration of the pace of life reinforce each other and produce "an ever-increasing pressure for further acceleration" (Hollstein & Rosa, 2023, p. 711; Rosa, 2013). Thus, for employees to maintain their employability, continuous change requires continuous updates of their knowledge and skills (Kubicek et al., 2015). Although increased learning can be perceived as a positive challenge (e.g., Obschonka et al., 2012), intensified learning demands on employees have been found to lead, for example, to feelings of inadequacy (a dimension of burnout) (Lehtiniemi et al., 2023), and overly high or low learning demands to lower work engagement (Mauno et al., 2024). In Europe, psychosocial risks at work are a major concern, and absences from work due to mental ill-health are on the rise (Eurofound, 2023). According to a large Finnish case-control study (n=36,879) white-collar employees were at an increased risk for premature retirement due to mental disorders, especially mood disorders (Karolaakso et al., 2020). They propose that while contemporary working life has offered employees opportunities, non-manual work, which is often related to white-collar positions, has become psychosocially more demanding (Karolaakso et al., 2020). While personal-level resources play an

important role, career sustainability is not likely to depend solely on intra-individual characteristics and resources, but also on the surrounding environment and resources.

This longitudinal study, aimed assessing the quality and development of occupational well-being over a four-year follow-up, focuses on highly educated Finnish employees in various fields. Person-centered methods have been infrequently utilized in occupational well-being studies and even less so in studies on transitions between occupational well-being profiles (Mäkikangas & Kinnunen, 2016). As suggested by Mäkikangas and colleagues (2016a), we study negative (burnout) and positive (work engagement) experiences simultaneously to gain a better understanding of the phenomenon. The study period includes the time of the COVID-19 pandemic, which significantly accelerated the need for employees to learn and adapt to digital tools and practices in the workplace (Holsstein & Rosa, 2023). Hence, we want to pursue perceived learning climate as a potential organizational-level resource. To the best of our knowledge, neither longitudinal approaches nor person-centered methods have been applied in research on organizational learning climate as a predictor of occupational well-being among highly educated employees. The theoretical models, hypotheses, and main constructs used in the study are introduced below.

Theoretical Background

Sustainable Careers and Conservation of Resources

We examine highly educated employees through the sustainable careers framework (De Vos et al., 2020). The model integrates individual agency and the need for adaptation during one's career. It considers multiple factors affecting career sustainability including phases and situations which over time shape individual careers (De Vos et al., 2020). We also utilize the conservation of resources (COR) theory (Hobfoll, 1989), embedded in the framework of sustainable careers (De Vos et al., 2020). The COR theory assumes that individuals obtain and retain resources (Hobfoll, 2001) that help them cope with challenging times during their career. A career that motivates and allows self-actualization is likely to lead to a better person-career fit that is indicated by healthiness, happiness, and productivity among both employees and stakeholders (De Vos et al., 2020; Martela & Pessi, 2018). For example, for leaders, motivation to lead has been found to be a personal-level resource promoting career sustainability in terms of occupational well-being and follower satisfaction (Auvinen et al., 2020, 2021). While personal-level resources and a proactive approach to career sustainability are important, employee career sustainability is also nurtured by resource-rich environments (De Vos et al., 2020; Westman et al., 2004).

Even if, based on their experiences and goals, people value certain resources differently (Halbesleben et al., 2014), working in a supportive environment is likely to encourage resource acquisition rather than resource protection (Hobfoll et al., 2018), not to mention resource loss, among most employees. Due to the cumulative nature of resources (i.e., resource caravans), resource-loss cycles can create a situation where already diminished resources further diminish (De Vos et al., 2020). While we encourage employees to engage, for example, in learning activities and continuous professional development, their efforts should be simultaneously supported (Lehtiniemi et al., 2023). Environmental conditions supporting or threatening resources have been also referred to as resource passageways

(Hobfoll, 2011). In this study occupational well-being (i.e., low burnout, high work engagement), reflecting the dimensions of health and happiness in the model, is considered an important personal resource for career sustainability (De Vos et al., 2020). We also study whether a supportive organizational learning climate, as a possible contextual resource, could foster occupational well-being, and thus be part of the resource enrichment process in the career sustainability of highly educated employees.

Occupational Well-being as an Indicator of Happiness and Health

Burnout appears to be more strongly associated with health problems whereas work engagement is more strongly connected to motivational outcomes (Bakker et al., 2023). People who suffer from burnout are likely to experience exhaustion, cynicism, and reduced professional efficacy (Maslach et al., 2001). The latter is also referred to as a feeling of inadequacy (Salmela-Aro et al., 2010; Feldt et al., 2014). Exhaustion manifests itself as feelings of strain and lowered emotional and physical resources, whereas cynicism refers to a distant attitude towards work, and inadequacy to feelings of lack of achievement, productivity, and competence on the job (Maslach et al., 2001; Salmela-Aro et al., 2010). In turn, work engagement comprises three dimensions: vigor (determination when facing hardships and energy while working), dedication (strong involvement and positive feelings towards work), and absorption (deep concentration and immersion in one's work) (Schaufeli et al., 2002, 2006). Burnout and work engagement are considered as negative and positive forms of occupational well-being (e.g., Mäkikangas et al., 2016a). Burnout is considered to reflect low pleasure and low arousal and work engagement high pleasure and high arousal (Bakker & Oerlemans, 2011; Russell, 1980; Warr, 1990).

It has been discussed whether, in occupational well-being, work engagement is always positive. For example, a recent meta-analysis found some overlap with workaholism (Di Stefano & Gaudiino, 2019). Taris et al. (2010) concluded that absorption is associated with both, with engaged people being intrinsically "pulled" towards work (thereby experiencing a positive affect) and workaholics being "pushed" to work (a negative affect). Bereznowski et al. (2023) suggested that work engagement could lead to burnout through work addiction. Person-centered studies conducted on heterogeneous samples of employees, similar to ours, found work engagement, burnout, and workaholism to exist both in separate profiles (e.g., Mäkikangas et al., 2015; Salanova et al., 2014) and simultaneously (Moeller et al., 2018). Studies among specific groups such as social workers (Lombardero-Posada et al., 2023), teachers (Gillet et al., 2018; Salmela-Aro et al., 2019) and guidance counselors (Rantanen et al., 2023) found profiles in which work engagement and burnout and / or workaholism occurred simultaneously. In addition to these studies indicating that negative and positive forms of well-being can be experienced at the same time, other studies have found occupational well-being profiles to remain similar over time (e.g., Mäkikangas et al., 2016b; Rantanen et al., 2023). This leads us to our first hypotheses:

H1a *The same number of occupational well-being profiles that retain their shape are likely to be identified at each measurement point during a four-year follow-up (within-sample stability).*

H1b *The identified profiles are likely to show differing levels of overall occupational well-being and in at least one of these profiles higher burnout and higher work engagement are likely to occur simultaneously.*

In a systematic review by Mäkikangas et al. (2016a) three categories of employee well-being development were outlined, some emphasizing habitual stability, some changes via maturation and growth, and some changes in response to changes in resources. While burnout and work engagement have been found to be relatively stable over time (e.g., Feldt et al., 2014; Seppälä et al., 2009), the findings of the review favored theories emphasizing change in employee well-being over time. However, follow-up length could play a role (i.e., shorter time lags indicating more change; Mäkikangas et al., 2016a). A longitudinal person-centered study utilizing transition analysis and profiling employee well-being indicators found that employees were likely to maintain their profiles rather than move to another profile during the 18-month follow-up (Harju et al., 2023). Another study, which used three-year and seven-year time-lags, found that employees in the high profile of job-related affective well-being were likely to remain in that profile whereas employees in the low profile were more likely to move to the better profile during either of the follow-ups (Mäkikangas et al., 2016b). The data in both studies were collected before COVID-19. A study among Finnish employees showed that occupational well-being increased during the first phase of COVID-19 but deteriorated during the second phase (Kaltiainen & Hakanen, 2022). Based on the theoretical background as well as empirical evidence, we hypothesize the following:

H2 *While most of the highly educated employees will maintain their initial occupational well-being profile, profile transitions are also likely to occur during the follow-up.*

Supportive Learning Climate as a Possible Organizational Resource for Employee Well-being

We investigate employees' perceptions of the current state of the learning climate (LC) in their organization by using the three dimensions introduced by Nikolova et al. (2014). In the first, facilitative LC, the organization is perceived as providing resources, training, and appealing educational facilities for learning; in the second, appreciative LC, the employees perceive themselves as appreciated and rewarded by their organization if they participate in activities that promote learning and professional development; in the third, error-avoiding LC, employees perceive that mistakes should be avoided, and that the organizational climate induces anxiety about discussing work-related problems (Nikolova et al., 2014). Perceptions can be shaped by individual differences and needs (e.g., Mäkikangas et al., 2015), and thus have an impact on what is experienced as supportive. Here, based on Nikolova et al.'s (2014) theoretical work, higher facilitative LC and appreciative LC, and lower error-avoiding LC reflect a learning climate that is perceived as more supportive. However, appreciative LC contains the element of receiving positive attention because of professional development (Nikolova et al., 2014). This, in the face of contemporary working life demands (Kotera & Correa Vione, 2020; Kubicek et al., 2015; Rosa, 2003), might be perceived by some employees as pressuring rather than supporting or motivating them.

LC dimensions have previously been studied as organizational resources, for example, with regard to learning outcomes: in the context of work restructuring (i.e., conditions of change and requirements to learn new), facilitative LC was found to be an important predictor under conditions of high restructuring whereas appreciative LC appeared more effective for learning outcomes when work restructuring was low (Nikolova et al., 2016). Thus, it is possible that, depending on the prevailing situational factors, the different dimensions of learning climate play a different role. Nikolova et al. (2014) found a correlation of better learning climate with higher vigor; however, they acknowledged that longitudinal research is needed to investigate their causal associations. In addition to Nikolova et al.'s learning climate measure, a positively experienced learning climate has been studied cross-sectionally among students in relation to better work engagement and job satisfaction (e.g., Lases et al., 2019) and lower burnout (e.g., Dyrbye et al., 2009). In another study, supportive cues from management (i.e., supervisory recognition and praise in a demanding work environment) were likely to enhance occupational well-being and make employees to "feel liberated in a resource gain spiral" (Lee et al., 2022, p. 12). In a study utilizing latent transition analysis, also used in our study, increased job resources (supportive organizational climate) were associated with favorable but not unfavorable job-related affective well-being profile transitions (Mäkikangas et al., 2016b).

Viewed from a personal resource perspective, occupational well-being can remain stable yet also be exposed to changes due to prevailing conditions, such as changes in other resources (Hobfoll, 1989; Mäkikangas et al., 2016a). Overall, a recent review on burnout and work engagement showed that low job resources together with high demands are more likely to lead to burnout while high resources together with challenge demands are more likely to lead to work engagement (Bakker et al., 2023), thereby indicating the need for different resources in career sustainability. We propose that the perceived learning climate in the work environment is likely to impact other resources (here occupational well-being) either positively or negatively, and hence the following hypotheses:

H3 *High facilitative LC is likely to predict highly educated employees moving to a more favorable occupational well-being profile whereas low facilitative LC is likely to predict highly educated employees moving to a less favorable occupational well-being profile.*

H4 *High appreciative LC is likely to predict highly educated employees moving to a more favorable occupational well-being profile whereas low appreciative LC is likely to predict highly educated employees moving to a less favorable occupational well-being profile.*

H5 *Low error-avoiding LC is likely to predict highly educated employees moving to a more favorable occupational well-being profile whereas high error-avoiding LC is likely to predict highly educated employees moving to a less favorable occupational well-being profile.*

Method

Participants

The original data for this longitudinal study were collected in 2017 (T1) and in two subsequent follow-ups in 2019 (T2) and 2021 (T3). The sample consisted of highly educated employees who were (a) members of four Finnish trade unions (the Finnish Union of University Professors, the Finnish Union of University Researchers and Teachers, the Finnish Business School Graduates, and the Academic Architects and Engineers in Finland) or (b) enrolled on an Executive Master of Business Administration (EMBA) program at the time. Participants from the EMBA program represented various sectors (e.g., services, finance). Invitations to participate were sent by email, and responses received from 2135 union members and 161 EMBA program participants at T1. Participants who informed us at the baseline or T2 measurements that they did not want to continue participating in the follow-up were not contacted. In 2019 (T2) 746 of 1051 participants responded; in 2021 (T3) 641 of 1028 participants responded.

The present study sample comprised 442 participants who met the eligibility criteria for this study (completion of the survey concerning the main variables at all three time points, high level of education, and active work life status). Of these, 267 (60%) were working as professionals in their field and 175 had a job that included formal leadership duties at T1. A slightly larger proportion of the participants identified as women ($n=238$, 54%). Participants were aged 25–64 years at T1 ($M=45.99$, $SD=9.46$) and the number of hours worked per week at T1 varied from 15 to 67 ($M=43.41$, $SD=7.23$). The sample consisted of 72 professors (16.3%), 168 other university academics and researchers (38%), 87 business school graduates (19.7%), 87 technical academics (19.7%), and 28 other participants (6.3%; EMBA, various fields). The number of years worked for the current employer at T3 varied between 0 and 44 years ($M=13.38$, $SD=10.02$). 330 participants (75%) did not change their employer during the follow-up. Information on the indicators of occupational well-being was missing completely at random ($\chi^2(50)=29.90$, $p=.989$). Among the background variables, leadership positions were underrepresented ($\chi^2(1)=89.29$, $p<.001$) compared to the original data. In addition, participants in the original sample were somewhat older ($M=49.20$, $SD=0.54$, $t(2283)=5.85$, $p<.001$) and reported slightly longer weekly working hours ($M=44.61$, $SD=8.83$), $t(2124)=2.61$, $p<.01$).

Measures

Occupational well-being was measured at T1, T2, and T3 with two indicators: burnout (three subdimensions) and work engagement. *Burnout* was measured using a 9-item version of the Bergen Burnout Inventory (BBI-9; Salmela-Aro et al., 2010; see also Feldt et al., 2014: 3 items for exhaustion, e.g., 'I often sleep poorly because of the circumstances at work'; 3 items for cynicism, e.g., 'I feel that I have gradually less to give'; and 3 items for inadequacy, e.g., 'My expectations to my job and to my performance have reduced'). The answers were given on a 6-point scale (1 = totally disagree and 6 = totally agree). *Work engagement* was measured with three items from the Utrecht Work Engagement Scale (UWES-3; Schaufeli et al., 2002; Seppälä et al., 2009): 'At my work, I feel that I am bursting with energy' (vigor); 'I am enthusiastic about my job' (dedication); and 'I am immersed

in my work' (absorption). Participants responded to each item on a 7-point scale (1 = never and 7 = daily). Lower burnout scores and higher work engagement scores indicate better occupational well-being.

Perceived learning climate was measured at T1 and T2 using the Learning Climate Scale (LCS; Nikolova et al., 2014: 3 items for facilitation, e.g., 'My organization provides sufficient resources to develop my competences'; 3 items for appreciation, e.g., 'In my organization, employees who make effort to learn new things, earn appreciation and respect'; and 3 items for error avoidance, e.g., 'In my organization, employees do not dare to discuss mistakes'). Answers were given on a 5-point scale (1 = strongly disagree and 5 = strongly agree). Higher scores for a facilitative and appreciative learning climate and lower scores for error-avoiding indicate a more supportive perceived learning climate.

Control variables included weekly working hours (in hours), age (in years), gender (0 = female, 1 = male), occupational position (0 = professional, 1 = leader), occupational context (0 = others, 1 = university), and whether one has stayed with the same employer throughout the follow-up (0 = has stayed, 1 = has changed). Control variables were selected based on correlation analyses and previous research findings: for example, overly long working hours have been associated with adverse health consequences (e.g., Geurts et al., 2013; Kivimäki et al., 2015). Higher status jobs (e.g., Rollero et al., 2016) and job change (e.g., Mäkikangas et al., 2016a) have been associated with better occupational well-being. Findings on the association of occupational well-being with age and gender have been more conflicting (e.g., Rollero et al., 2016; Zacher & Schmitt, 2016).

Statistical Analyses

The preliminary statistical analyses were conducted with IBM SPSS Statistics 27 Software. The reliability of the variables was tested and intercorrelations among the main variables and background variables were studied. The remaining analyses were conducted with Mplus 8.9 (Muthén & Muthén, 1998–2017). We decided to use scale scores for the measures, as our preliminary analyses suggested adequate reliability ($\alpha = 0.68$–0.89). We estimated Latent Profile Analyses (LPA) and Latent Transition Analyses (LTA) following the procedures outlined by Morin and Litalien (2019). To avoid local maxima, we conducted LPAs using at least 3,000 sets of random start values, retained the 100 best solutions for final stage optimization, and used 100 iterations (Morin & Litalien, 2019). For the longitudinal analyses these values were increased to 7,000, 1,000, and 200, respectively. Models were estimated with Robust Maximum Likelihood Estimator (MLR). Missing data (considering background variables) were handled using Full Information Maximum Likelihood procedures (FIML; Muthén & Muthén, 1998–2017).

We conducted time-specific LPAs to estimate profiles for each measurement point separately. Means of the indicators were freely estimated in all profiles. To avoid zero variances and hence convergence problems, variance constraints were set to > 0.01. The estimation was conducted by adding groups one at a time. To decide on the best fitting model, we considered the reasonability of the content and fit indices (lower AIC, BIC, aBIC, higher entropy and classification accuracy, and significant BLRT). The aLMR and the VLMR tests were not considered, as the TECH11 command in Mplus was not available with the model constraints used ($v > 0.01$). There appears to be a broadly shared consensus that researchers should pay attention to theoretical and content reasonability when deciding the number

of profiles rather than selecting the model based on the mechanical application of recommended fit indices (e.g., Diallo et al., 2016; Marsh et al., 2009). After deciding on the final number of profiles for each measurement point, the profile content was tested in relation to the background variables by utilizing the DCAT auxiliary procedure (Asparouhov & Muthén, 2014; Vermunt, 2010).

Next, the within-sample stability (see Kam et al., 2016) and longitudinal measurement invariance were studied. By estimating all three measurement points in the same model, we conducted a longitudinal LPA and tested profile similarity (Kam et al., 2016). The process of identifying the best longitudinal LPA solution comprises four steps (four models), in which the current model is compared to the previous (less constrained) model and, based on the statistical fit indices, it is decided whether the similarity assumption is accepted (Morin et al., 2016). We also compared models using the chi-square difference test. First, we studied configural similarity, which assesses whether the same number of profiles are identified at all three measurement points (i.e., the freely estimated model). Second, structural similarity was studied to assess whether the within-profile levels on the indicators remained the same at all measurement points (i.e., the model with equal means). The next steps would have included studying dispersion similarity (i.e., the model with equal variances) and distributional similarity (i.e., the model with equal group sizes). The start values from the selected final solution were used in the subsequent analyses to keep the nature of the profiles unchanged (Morin et al., 2019).

Next, the final model (the most similar longitudinal LPA solution) was converted to LTA (Morin & Litalien, 2019; see also Collins & Lanza, 2009). With LTA, the relationship between latent class variables at different time points is estimated through a multinomial logistic regression (Asparouhov & Muthén, 2014). The within-person stability (Kam et al., 2016) was studied by considering the transition probabilities.

Finally, the 3-step method (Vermunt, 2010; Asparouhov & Muthén, 2014) was used to predict profile transitions with covariates. Separate analyses were conducted for the T1 covariate predicting the T1-T2 transitions and T2 covariate predicting the T2-T3 transitions (R3STEP auxiliary procedure; see Asparouhov & Muthén, 2014). Two analyses were conducted per predictor (covariate) to assess whether the association remained after adding control variables to the model. A significant p-value indicates that the covariate has predictive power for a specific transition from one profile to another (reference group; maintenance of the same profile). Odds ratios (OR) indicate the odds that an outcome will occur given exposure to a predictor versus the odds of the outcome occurring in the absence of that predictor (Muthen & Muthen, 1998–2017; Szumilas, 2010). An OR of 1 means that the exposure to a predictor will not affect the odds of the outcome, whereas an OR higher or lower than 1 means that the predictor is associated with higher or lower odds that the outcome will occur (Muthen & Muthen, 1998–2017; Szumilas, 2010). The 95% confidence interval (CI) indicates the accuracy of the result.

Results

Descriptive Results

The correlational analysis showed that occupational well-being dimensions (burnout and work engagement) remained relatively stable over the 4-year period (test-retest $r=0.31$–0.60). Overall, a more supportive learning climate correlated with better occupational well-being (see details in Table 1). With respect to the background variables, higher weekly working hours correlated with higher levels of exhaustion and work engagement at each measurement point, and with lower levels of cynicism and inadequacy at T1. Higher age correlated with higher levels of exhaustion at T1 and T2. Gender (i.e., identifying as a male) correlated with lower levels of error-avoiding LC at T2 and with lower levels of exhaustion and work engagement at each measurement point. Occupational background (position and context) also correlated with the studied variables. Being in a leadership position correlated with a more supportive perceived learning climate (all three dimensions), higher levels of exhaustion at T1, lower levels of cynicism and inadequacy at T1, and higher levels of work engagement at T2 and T3. Working in a university context correlated with less supportive levels of perceived learning climate (all three dimensions, except facilitative LC at T2) and higher levels of exhaustion at each measurement point.

Within-Sample Stability: Identifying Profiles of Occupational Well-being

As shown in Table 2, we estimated five LPAs for each measurement point. The BLRT test was significant for every estimation, showing improvement of fit after adding one more class; this can occur if of the parameters added contain more of the information present in the dataset (e.g., Ferguson et al., 2020). The BIC value suggested the four-group solution for T1 and T3, whereas for T2 the BIC value did not increase (i.e., deteriorate) even when estimating the five-group solution. A high classification accuracy was associated with both the three-group (92.3–95.2%) and four-group (87.6–98.7%) solutions. The highest entropy values were found for the three-group solutions (0.85-0.88). Although the BIC value supported the four-group or five-group rather than three-group solution, the fit indices did not markedly differ, and content reasonability led us to choose the three-group solution. While the four-group or five-group solutions would have included a profile more clearly representing low occupational well-being, they would have left us with profiles of high occupational well-being that were excessively similar.

Comparison of the first longitudinal LPA model (i.e., configural similarity) and the second longitudinal LPA model (i.e., structural similarity) indicated that we should run LTA with the first model without invariance constraints. Although we could not set the means equal for the different measurement points, the shape in general remained similar (see Figs. 1 and 2). Thus, *H1a* was supported, and it was possible to label the qualitatively distinct profiles in the same manner for each measurement point.

H1b was supported, as we identified profiles that showed differing levels of occupational well-being, and higher work engagement was characterized in profiles that were also higher in burnout dimensions. We labeled Profile 1 as *burnout*, *lowered engagement*. This profile had the most adverse occupational well-being levels compared to the other profiles. Participants in this profile reported higher burnout and lower work engagement than the sam-

ple mean. Profile 2 was labeled *average exhaustion*, *high engagement*. These participants reported somewhat lower cynicism and inadequacy and a level of exhaustion that was on the emerging level but did not differ from the sample mean. Also, the level of work engagement did not differ much from the sample mean. Profile 3, with high occupational well-being scores, was labeled *low burnout*, *very high engagement*.

Latent status prevalence is reported in Table 3. Most participants (43–53%) were in Profile 2 at each measurement point. More (27–42%) were in Profile 1 (the least favorable occupational well-being) than in Profile 3 (7–21%), which showed the most favorable occupational well-being. The most notable difference between these latent status prevalences was seen at T3, the end of the follow-up, when only 7% of the participants were in Profile 3 whereas 39% were in Profile 1. Background variables (age, weekly working hours, gender, occupational position, occupational context) were explored in relation to the T1 profiles: Profile 1 was found to contain fewer leaders (32%) than Profile 2 (44%) or Profile 3 (51%).

Within-Person Stability: Estimating Transition Probabilities

The possibility to interpret the profiles in the same manner for each measurement point allowed us to examine the profile stability and transitions. *H2* was supported as most of the participants maintained their profiles, although transitions to other profiles also occurred. Table 3 shows the transition probabilities and Fig. 3 the expected numbers of participants maintaining their profiles or transitioning (the numbers may differ slightly as in the transition probabilities provided by LTA all the time-specific profiles were included in the same model whereas the graphically displayed numbers of participants transitioning from T1-T2 and from T2-T3 were estimated in separate analyses). The probability odds indicate that, with two exceptions (Profile 1 at T1 to Profile 2 at T2 and Profile 3 at T1 to Profile 2 at T2; see Table 3), all the transitions can be considered statistically significant. Transitions occurred to occupational well-being profiles that were both better and worse than those at the previous measurement point (initial status at T1 or T2).

In the case of T1-T2 transitions with *Profile 1 as the initial status*, 39.2% of members were expected to move to Profile 2 and 9.2% to move to Profile 3. The trend was the same for T2-T3 (20.1% and 2%, respectively), although here the within-person stability was higher (77.8%) than in the first part of the follow-up (T1-T2, 51.6%). In the case of T1-T2 transitions with *Profile 2 as the initial status*, 7.7% of members were expected to move to Profile 1 and 21.8% to move to Profile 3. Interestingly, the opposite was found for T2-T3, as 33.7% of members were expected to move to Profile 1 and only 1.4% to move to Profile 3. The within-person stabilities remained nearly the same: 70.6% (T1-T2) and 64.9% (T2-T3). Finally, investigation of the T1-T2 transitions with *Profile 3 as the initial status* showed that 33.6% of members were expected to move to Profile 2 and 14.1% to move to Profile 1. The within-person stability was 52.3% between T1 and T2 but only 28.3% between T2 and T3, as transitioning from Profile 3 to Profile 2 was more common (67.7%). In other words, those in the most favorable occupational well-being group (Profile 3) at T2 were more likely to move to a somewhat less favorable occupational well-being group (Profile 2) than to remain in the most favorable occupational well-being group (Profile 3). In addition, 4% of members were expected to move to Profile 1 between T2 and T3.

Table 1 Means (*M*), standard deviations (*SD*), reliabilities (α), and Pearson's correlations for the study variables ($n=442$)

Variable	M (SD)	α	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1. T1 EXH	3.05 (1.15)	0.75	-																
2. T1 CYN	2.43 (1.16)	0.82	0.33***	-															
3. T1 INA	2.72 (1.30)	0.78	0.35***	0.79***	-														
4. T1 WE	5.55 (1.10)	0.83	−0.13**	−0.62***	−0.57***	-													
5. T1 FLC	2.96 (0.89)	0.89	−0.13**	−0.31***	−0.36***	0.27***	-												
6. T1 ALC	2.71 (0.77)	0.72	−0.18***	−0.42***	−0.45***	0.32***	0.62***	-											
7. T1 EALC	2.82 (0.92)	0.86	0.17***	0.39***	0.45***	−0.28***	−0.28***	−0.40***	-										
8. T2 EXH	3.08 (1.13)	0.74	0.66***	0.14**	0.20***	−0.10*	−0.09*	−0.16***	0.14**	-									
9. T2 CYN	2.40 (1.13)	0.83	0.24***	0.45***	0.37***	−0.38***	−0.16***	−0.24***	0.20***	0.39***	-								
10. T2 INA	2.65 (1.22)	0.78	0.23***	0.40***	0.45***	−0.30***	−0.21***	−0.26***	0.24***	0.32***	0.77***	-							
11. T2 WE	5.57 (1.13)	0.86	−0.13**	−0.40***	−0.36***	0.62***	0.22***	0.26***	−0.18***	−0.14**	−0.66***	−0.56***	-						
12. T2 FLC	3.04 (0.89)	0.89	−0.09	−0.14**	−0.15**	0.13**	0.51***	0.38***	−0.14**	−0.18***	−0.31***	−0.32***	0.31***	-					
13. T2 ALC	2.75 (0.75)	0.68	−0.19***	−0.22***	−0.25***	0.18***	0.34***	0.51***	−0.28***	−0.27***	−0.39***	−0.40***	0.33***	0.66***	-				
14. T2 EALC	2.85 (0.91)	0.86	0.20***	0.15**	0.21***	−0.11*	−0.20***	−0.21***	0.45***	0.27***	0.32***	0.42***	−0.22***	−0.29***	−0.44***	-			
15. T3 EXH	2.99 (1.03)	0.68	0.60***	0.13**	0.15**	−0.00	−0.08	−0.07	0.06	0.60***	0.19***	0.17***	−0.05	−0.12*	−0.17***	0.14**	-		
16. T3 CYN	2.56 (1.15)	0.84	0.24***	0.33***	0.24***	−0.27***	−0.10*	−0.13**	0.13**	0.24***	0.54***	0.43***	−0.39***	−0.19***	−0.28***	0.18***	0.39***	-	

Table 1 (continued)

Variable	M (SD)	α	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
17. T3 INA	1.72 (1.22)	0.78	0.22***	0.28***	0.31***	−0.25***	−0.11*	−0.15**	0.18***	0.24***	0.42***	0.47***	−0.32***	−0.18***	−0.25***	0.25***	0.36***	0.77***	-
18. T3 WE	5.33 (1.25)	0.89	−0.03	−0.22***	−0.23***	0.50***	0.10*	0.14**	−0.11*	−0.08	−0.37***	−0.32***	0.55***	0.14**	0.15**	−0.09	−0.11*	−0.59***	−0.54***

Notes: * $p<.05$, ** $p<.01$, *** $p<.001$, Significance tests are two-tailed

EXH = Exhaustion, CYN = Cynicism, INA = Inadequacy, WE = Work engagement, FLC = Facilitative learning climate, ALC = Appreciative learning climate, EALC = Error-avoiding learning climate

Table 2 Time-specific LPAs and longitudinal models

Model	LL	FP	SC	AIC	BIC	aBIC	Entropy
Time-specific LPAs							
Time 1 (two-group solution)	-2432.245	17	1.068	4898.490	4968.043	4914.092	0.850
Time 1 (three-group solution)	**-2312.912**	**26**	**1.082**	**4677.824**	**4784.199**	**4701.687**	**0.876**
Time 1 (four-group solution)	-2243.984	35	0.913	4557.968	4701.164	4590.090	0.848
Time 1 (five-group solution)	-2219.412	44	0.969	4526.824	4706.842	4567.206	0.832
Time 2 (two-group solution)	-2410.681	17	1.118	4855.362	4924.914	4870.964	0.819
Time 2 (three-group solution)	**-2285.764**	**26**	**1.126**	**4623.529**	**4729.903**	**4647.391**	**0.851**
Time 2 (four-group solution)	-2239.337	35	1.244	4548.673	4691.869	4580.795	0.829
Time 2 (five-group solution)	-2206.013	44	1.041	4500.026	4680.044	4540.408	0.838
Time 3 (two-group solution)	-2473.133	17	1.223	4980.266	5049.819	4995.869	0.799
Time 3 (three-group solution)	**-2365.378**	**26**	**1.057**	**4782.756**	**4889.130**	**4806.618**	**0.864**
Time 3 (four-group solution)	-2300.272	35	1.184	4670.544	4813.740	4702.666	0.818
Time 3 (five-group solution)	-2274.125	44	1.259	4636.251	4816.268	4676.633	0.832
Longitudinal LPAs (within-sample stability)							
Configural similarity	**-6960.847**	**78**	**1.084**	**14077.694**	**14396.817**	**14149.280**	**0.865**
Structural similarity	-6996.993	54	1.130	14101.987	14322.917	14151.546	0.851
Conversion to LTA	-6840.059	50	0.975	13780.117	13984.683	13826.006	0.873

Notes: N=442. LL=loglikelihood; FP=free parameters; SC=Correction factor for robust MLR; AIC=Akaike information criterion; BIC=Bayesian information criterion; aBIC=sample-size adjusted BIC. BLRT (=Bootstrap likelihood ratio test) remained significant in each time-specific LPA. The chi-square difference between the less constrained model (configural similarity) and more constrained model (structural similarity) is significant (p<.001). Selected models in bold. Although within-profile means are slightly different, the shape remains similar across different measurement points. The start values from the final solution were used in the main analyses to ensure the nature of the profiles remained unchanged

Perceived Learning Climate as a Predictor of Occupational Well-being Profile Transitions

The results of the multinomial logistic regression analyses (the 3-step method) are reported in Table 4 (separate analyses for T1-T2 and T2-T3). None of the dimensions of perceived learning climate (facilitative LC, appreciative LC, or error-avoiding LC) predicted any transitions during the first part of the follow-up (T1-T2). However, after controlling for background variables, perceived learning climate had a predictive role during the second part of the follow-up (T2-T3).

H3 was partially supported, as the expected transitions to a less favorable occupational well-being profile were detected in two analyses. Thus, the analysis with facilitative LC at

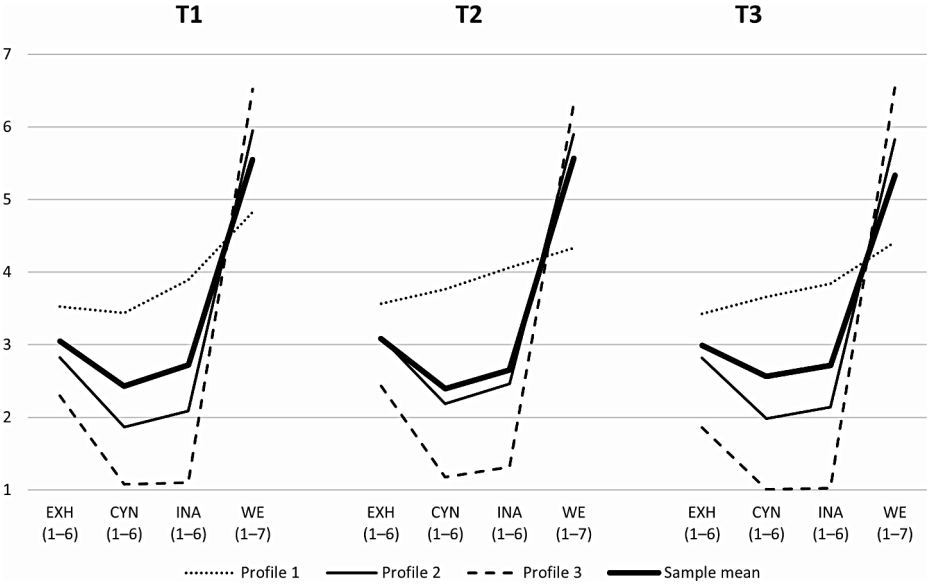

Fig. 1 Time-specific LPAs (raw scores; item range in parenthesis). Notes: EXH = exhaustion, CYN = cynicism, INA = inadequacy, WE = work engagement; Profile 1 = burnout, lowered engagement; Profile 2 = average exhaustion, high engagement; Profile 3 = low burnout, very high engagement

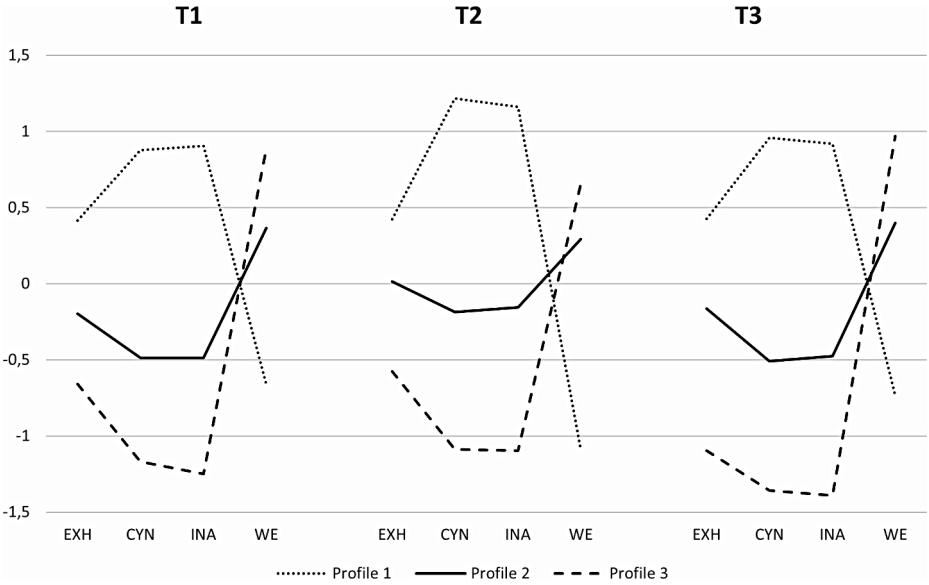

Fig. 2 Time-specific LPAs (standardized scores). Notes: EXH = exhaustion, CYN = cynicism, INA = inadequacy, WE = work engagement; Profile 1 = burnout, lowered engagement; Profile 2 = average exhaustion, high engagement; Profile 3 = low burnout, very high engagement

Table 3 Latent status prevalence and transition probabilities (within-person stability) for occupational well-being (burnout, work engagement) among highly educated employees over three time points (n=442)

	Latent status prevalence (n)			τ estimates				τ estimates			
					Time 1 to Time 2				Time 2 to Time 3		
	Profile 1	**Profile 2**	**Profile 3**		**Profile 1**	**Profile 2**	**Profile 3**		**Profile 1**	**Profile 2**	**Profile 3**
Time 1	0.422 (187)	0.431 (191)	0.147 (65)	**Profile 1**	0.516	0.392[a]	0.092	**Profile 1**	0.778	0.201	0.020
Time 2	0.272 (120)	0.519 (229)	0.209 (93)	**Profile 2**	0.077	0.706	0.218	**Profile 2**	0.337	0.649	0.014
Time 3	0.395 (174)	0.533 (236)	0.072 (32)	**Profile 3**	0.141	0.336[b]	0.523	**Profile 3**	0.040	0.677	0.283

Notes: Profile 1 = burnout, lowered engagement; Profile 2 = average exhaustion, high engagement; Profile 3 = low burnout, very high engagement

Latent status prevalence (%) and transition probabilities are reported from the LTA that includes each three measurement point in the same model

Non-significant transitions according to the probability odds: [a]Odds ratio (0.760) and 95% confidence interval (0.527, 1.096); [b]Odds ratio (0.643) and 95% confidence interval (0.323, 1.283)

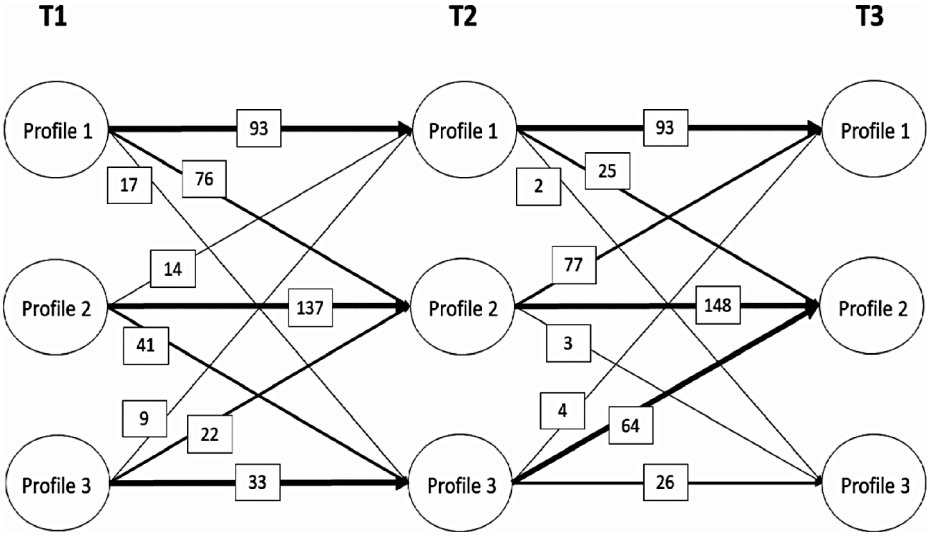

Fig. 3 Transition paths and transition prevalences (expected numbers of people transitioning shown in the figure) were estimated in separate analyses for T1-T2 and T2-T3 using the 3-step method. Notes: Profile 1 = burnout, lowered engagement; Profile 2 = average exhaustion, high engagement; Profile 3 = low burnout, very high engagement

T2 as a predictor showed that people with a higher level of facilitative LC were more likely to remain in Profile 3 at T3, whereas those with lower facilitative LC were more likely to have moved from Profile 3 to Profile 2 by T3. In all this transition was expected for 64 individuals. The second finding on facilitative LC at T2 showed a similar trend: people with a higher level of facilitative LC were more likely to remain in Profile 3 at T3, whereas those with lower facilitative LC were more likely to have move from Profile 3 to Profile 1 by T3.

Table 4 Perceived learning climate as a predictor of transition probabilities (multinomial logistic regression using the 3-step method)

Transition path	Predictors											
T1–T2	T1 FLC		T1 FLC with controls		T1 ALC		T1 ALC with controls		T1 EALC		T1 EALC with controls	
	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]
Profile 1 → 2	0.396 (0.236)	1.486 [0.936; 2.361]	0.436 (0.272)	1.547 [0.908; 2.635]	0.538 (0.283)	1.712 [0.983; 2.984]	0.586 (0.307)	1.798 [0.985; 3.280]	−0.264 (0.208)	0.768 [0.511; 1.154]	−0.181 (0.215)	0.834 [0.547; 1.272]
Profile 1 → > 3	0.059 (0.446)	1.061 [0.443; 2.545]	0.501 (0.439)	1.650 [0.698; 3.901]	0.655 (0.359)	1.925 [0.952; 3.890]	0.820 (0.526)	2.271 [0.810; 6.363]	0.109 (0.259)	1.115 [0.671; 1.853]	1.053 (0.586)	2.866 [0.908; 9.046]
Profile 2 → 1	−0.229 (0.436)	0.795 [0.338; 1.869]	−0.526 (0.586)	0.591 [0.187; 1.862]	−0.053 (0.481)	0.948 [0.369; 2.434]	−0.204 (0.553)	0.816 [0.276; 2.413]	−0.656 (0.484)	0.519 [0.201; 1.341]	-1.035 (0.892)	0.355 [0.062; 2.041]
Profile 2 → 3	0.018 (0.264)	1.019 [0.608; 1.707]	0.123 (0.315)	1.131 [0.610; 2.096]	0.091 (0.382)	1.095 [0.518; 2.315]	0.427 (0.430)	1.532 [0.660; 3.559]	−0.203 (0.294)	0.816 [0.459; 1.452]	−0.264 (0.327)	0.768 [0.404; 1.458]
Profile 3 → 2	0.617 (0.493)	1.854 [0.706; 4.869]	0.716 (0.590)	2.046 [0.644; 6.505]	0.128 (0.513)	1.137 [0.416; 3.109]	0.344 (0.727)	1.410 [0.339; 5.863]	−0.131 (0.497)	0.877 [0.331 2.325]	−0.491 (0.665)	0.612 [0.166; 2.253]
Profile 3 → 1	−0.828 (0.772)	0.437 [0.096; 1.984]	-1.286 (1.265)	0.276 [0.023; 3.300]	0.502 (0.706)	1.652 [0.414; 6.597]	0.670 (0.733)	1.955 [0.465; 8.220]	1.405* (0.689)	4.076 [1.057; 15.722]	1.301 (0.766)	3.672 [0.818; 16.476]
T2–T3	T2 FLC		T2 FLC with controls		T2 ALC		T2 ALC with controls		T2 EALC		T2 EALC with controls	
	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]
Profile 1 → 2	0.425 (0.408	1.530 [0.688; 3.401]	0.918 (0.814)	2.503 [0.508; 12.341]	0.501 (0.317)	1.650 [0.887; 3.072]	0.331 (0.490)	1.393 [0.534; 3.636]	−0.502 (0.438)	0.606 [0.256; 1.430]	−0.513 (0.653)	0.599 [0.166; 2.155]
Profile 1 →	−0.803 (0.558)	0.448 [0.150; 1.336]	0.181 (1.088)	1.199 [0.142; 10.109]	-1.011* (0.399)	0.364 [0.167; 0.796]	*-1.694*** (0.435)*	*0.184 [0.078; 0.431]*	1.586** (0.555)	4.886 [1.645; 14.509]	1.687 (0.995)	5.404 [0.769; 38.005]
Profile 2 → 1	0.064 (0.207)	1.066 [0.711; 1.598]	0.111 (0.221)	1.117 [0.725; 1.721]	0.026 (0.254)	1.027 [0.625; 1.688]	0.070 (0.354)	1.073 [0.535; 2.149]	0.173 (0.203)	1.188 [0.798; 1.769]	0.182 (0.223)	1.200 [0.775; 1.857]
Profile 2 → 3	*-4.395** (1.354)*	*0.012 [0.001; 0.175]*	*-80.896*** (0.998)*	*0.000 [0.000; 0.000]*	1.313 (0.712)	3.718 [0.921; 15.010]	1.562 (1.179)	4.766 [0.473; 48.021]	1.024 (0.946)	2.785 [0.436; 17.798]	*-160.867*** (1.254)*	*0.000 [0.000; 0.000]*

Table 4 (continued)

T2–T3	T2 FLC		T2 FLC with controls		T2 ALC		T2 ALC with controls		T2 EALC		T2 EALC with controls	
	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]	Est. (SE)	OR [CI]
Profile 3 →	−0.723* (0.292)	0.485 [0.274; 0.861]	−0.766* (0.346)	0.465 [0.236; 0.916]	−0.690 (0.419)	0.501 [0.221; 1.140]	−0.576 (0.473)	0.562 [0.223; 1.420]	0.416 (0.406)	1.517 [0.685; 3.360]	0.323 (0.426)	1.381 [0.599; 3.181]
Profile 3 → 1	-1.136 (0.934)	0.321 [0.051; 2.003]	*-2.360* (1.040)*	*0.094 [0.012; 0.725]*	−0.338 (0.832)	0.713 [0.140; 3.638]	−0.329 (1.240)	0.720 [0.063; 8.175]	-1.831 (0.982)	0.160 [0.023; 1.098]	-1.811 (1.289)	0.164 [0.013; 2.044]

Notes: N=442. OR=Odds ratio. CI=95% confidence interval. * p<.05, ** p<.01, *** p<.001. Reference group comprises individuals who maintained their profile. In italics=4≤individuals expected to transition

The start values from the final solution were used to ensure the nature of the profiles remained unchanged following the inclusion of predictors

Profile 1=burnout, lowered engagement; Profile 2=average exhaustion, high engagement; Profile 3=low burnout, very high engagement

FLC=Facilitative learning climate; ALC=Appreciative learning climate; EALC=Error-avoiding learning climate

Control variables include age, weekly working hours, gender, occupational position (professional/leader), occupational context (university/others), and whether participant has changed their job/employer

It should be noted that although the result is significant, in all only three individuals were expected to make this transition. The third finding on facilitative LC at T2, contrary to the hypothesis, showed that the higher their level of facilitative LC, the more likely individuals were to remain in Profile 2, and that the lower their level of facilitative LC, the more likely individuals were to have moved from Profile 2 to Profile 3 by T3, although in all only four were expected to make this transition.

H4 was not supported. According to the only finding on appreciative LC at T2 as a predictor, individuals were more likely to remain in Profile 1 if they reported a higher level of appreciative LC, while those reporting a lower level of appreciative LC were more likely to have moved from Profile 1 to Profile 3 by T3. Although the result is significant, in all only two individuals were expected to make this transition.

H5 was partially supported as one expected transition to a more favorable occupational well-being profile was detected when error-avoiding LC at T2 was a predictor. Individuals with higher error-avoiding LC were more likely to remain Profile 2, while those with a lower level of error-avoiding LC were more likely to have moved from Profile 2 to Profile 3 by T3. Again, only three people were expected to make this transition. Thus, the result should be interpreted with caution.

Discussion

Our aim was to study highly educated professionals and identify profiles which we assumed would differ by members' levels of occupational well-being indicators. Using a person-centered method allowed us to study whether people tend to remain in their initial profiles or transition to new profiles over time. The first study period was from 2017 to 2019 (T1-T2) and the second from 2019 to 2021 (T2-T3). We were interested in whether employees' perceived workplace learning climate predicts their transitions, and thus act as a possible organizational-level resource that could be part of the resource gain spiral process by nurturing the existing level of occupational well-being or fostering its positive development. We further studied whether a learning climate perceived as unsupportive could trigger or reinforce the resource loss cycle, manifested as a deterioration in occupational well-being.

Profiles with Simultaneous Occurrence of Burnout and Work Engagement

We identified three profiles of occupational well-being that maintained a similar shape across the three time points (2017, 2019, 2021) and found that they showed differing levels of occupational well-being. The 'low burnout, very high engagement' profile was clearly the most favorable profile in terms of occupational well-being while the 'burnout, lowered engagement' profile was the most unfavorable profile. The middle profile, characterized by 'average exhaustion, high engagement' was found to be an emergent level for one dimension of burnout (exhaustion) while cynicism and inadequacy were at a lower level and work engagement at a high level. Based on reviews by Mäkikangas et al. (2016a) and Bakker et al. (2023), most employees rate their occupational well-being positively. Consistent with these findings, our sample also exhibited high levels of work engagement, likely contributing to the absence of profiles with very low work engagement.

We found burnout and work engagement to co-exist within the same profile (in profiles of *burnout*, *lowered engagement* and *average exhaustion*, *high engagement*). Our results are in line with previous studies that have identified profiles with the simultaneous occurrence of burnout and work engagement (Lombardero-Posada et al., 2023; Moeller et al., 2018; Rantanen et al., 2023; Salmela-Aro et al., 2019). Although burnout and work engagement are seen as reflecting negative and positive forms of employee well-being (e.g., Mäkikangas et al., 2016a), meta-analytical studies indicate that work engagement could overlap with workaholism (Di Stefano & Gaudiino, 2019), a finding which might explain our results. For example, Bereznowski et al. (2023) discussed the possibility of work engagement leading to burnout through work addiction. In our study, higher weekly working hours correlated with higher work engagement and higher exhaustion but also with lower cynicism and inadequacy. Absorption is associated with both work engagement and workaholism: while the experience of being positively pulled towards work can be fulfilling, employees might need to remain mindful that "a positive pull" does not turn into "a negative push" (Taris et al., 2010), which in turn might be linked with exhaustion (see Rantanen et al., 2023).

The Development of Occupational Well-being during the Follow-up

When compared to 2017 (T1), the number of employees in the most unfavorable occupational well-being profile was lower in 2019 (T2), and when compared to 2019 (T2) it was higher in 2021 (T3). The number of employees in the most favorable occupational well-being profile was higher in 2019 than in 2017 and lower in 2021 than in 2019. The number of employees in the 'average exhaustion, high engagement' profile increased in 2019, whereas no notable change was observed between 2019 and 2021. Our results are in line with those of Rantanen et al. (2023) and Kaltiainen and Hakanen (2022), who found a decrease in occupational well-being after the beginning of the COVID-19 pandemic. Along with employees having to discontinue at least some of their hitherto normal social activities, the pandemic accelerated the need for digitalized tools and practices (Holsstein & Rosa, 2023), a situation which might have intensified employees' experiences of stress and increased their work-related demands, leading eventually to a health and motivation impairment process (Bakker et al., 2023)– in other words, leading to higher exhaustion, cynicism, and inadequacy, and / or lowered work engagement.

Further, we found employees to be more likely to remain in the most unfavorable and less likely to remain in the most favorable occupational profile during T2-T3 compared to T1-T2. Although clear transition activity (both towards better and worse occupational well-being) was evident, the employees were most likely to remain in their initial profile. However, an anomaly was detected during T2-T3, as more individuals were likely to transition to the 'average exhaustion, high engagement' profile from the 'low burnout, very high engagement' profile than to remain in this initial profile. Harju et al. (2023) found a high probability for employees remaining in their initial profile, as also reported earlier by Mäkikangas et al. (2016b), although only for those in the high and not those in the low well-being profile, a finding which highlighted a positive development. The data of both studies were collected before the pandemic, which may explain part of the divergent results. In addition, different length of time-lags, number of profiles, and measures of employee well-being could play a part.

The Complex Nature of Perceived Learning Climate

Although higher facilitative LC did not predict transitions to more favorable well-being groups, we found lower facilitative LC predict transitions to slightly less and clearly less favorable well-being groups when the initial profile was 'low burnout, very high engagement'. This means that higher facilitative LC was associated with maintaining the most favorable profile in terms of occupational well-being, supporting the resource perspective. According to the COR theory, individuals and organizations with higher resources are less vulnerable to resource loss than those who lack resources (Hobfoll, 2001; Hobfoll et al., 2018). Thus, higher facilitative LC might help in the maintenance of good occupational well-being, whereas low levels of facilitative LC (i.e., absence of one resource) might increase deterioration in occupational well-being (i.e., loss of another resource). We found one contradictory result: when the initial profile was 'average exhaustion, high engagement', lower facilitative LC predicted a transition to a slightly more favorable occupational well-being profile. Although the direction is towards slightly better well-being, the composition of the initial profile should be borne in mind– as mentioned earlier, while comprising good levels of the other three occupational well-being indicators, it is also characterized by emerging exhaustion. Employees in this group might benefit from a climate that allows them to focus on their work, which they are likely to find engaging, while not being eager to engage in new learning activities.

Based on the possible curvilinear relations, at a certain level the impacts of a possible resource might start to lessen or even become unfavorable rather than favorable (see Warr, 2007). This might also explain why higher facilitative LC was associated with the maintenance but not upward development of occupational well-being, and perhaps also why lower facilitative LC was associated with its upward development. Although COR theory links higher resources with resource gain in addition to maintenance (Hobfoll, 2001), it might as well be that higher facilitative LC as a possible resource was not salient enough to support the transition of these employees from the lowest occupational well-being profile (burnout, lowered engagement) to the higher occupational well-being profiles, and that the 'average exhaustion, high engagement' profile already comprises rather good levels of occupational well-being indicators (low cynicism and inadequacy, and high work engagement).

We did not find higher appreciative LC to predict transitions to more favorable occupational well-being profiles or lower appreciative LC to predict transitions to less favorable occupational well-being profiles. When the initial profile was 'burnout, lowered engagement', our contrary finding indicated that lower appreciative LC might predict a transition from the lowest to the highest occupational well-being profile. This means that higher appreciative LC was associated with remaining in the most unfavorable occupational well-being group. This raises the question of whether appreciative LC contains aspects that would make sustainable careers vulnerable in its presence. Our results might be explained by a perception of appreciative LC as more pressuring than supporting in the context of current working life demands (Kotera & Correa Vione, 2020; Kubicek et al., 2015; Rosa, 2003), meaning that employees might feel the need to push themselves even harder to gain approval in their organization and maintain their employability (De Vos et al., 2020; Nikolova et al., 2014). Nikolova et al. (2016) found appreciative LC to function as an important organizational resource supporting learning when employees were facing fewer changes in their environment whereas facilitative LC was found to become more important when restructuring was

high. Although the outcome measured here is different, if the need for resources changes to match one's context (Halbesleben et al., 2014), could it be that appreciative LC is perceived as more helpful and motivating when that context is more stable?

Finally, we found that lower error-avoiding LC might predict a transition from the 'average exhaustion, high engagement' profile to the 'low burnout, very high engagement' profile, which is slightly better in terms of occupational well-being. This indicates that some upward development in occupational well-being might occur for employees who are more likely to be "free" from having to work in a psychologically unsafe environment, and whose organizations would be more likely to utilize error-management instead of error-avoidance strategies (Nikolova et al., 2014). However, the evidence remains limited as lower error-avoiding LC did not associate with transitions to clearly or slightly better occupational well-being profiles when the initial profile was the lowest in terms of occupational well-being. In addition, higher error-avoiding LC did not predict transitions to either slightly or clearly less favorable groups.

Overall, comprehensive conclusions cannot be drawn as research on the learning climate as a predictor of burnout and work engagement among highly educated employees is scarce, and this study is the first to explore perceived learning climate as a predictor of employee well-being by utilizing transition analysis. Interestingly, we found perceived learning climate to act as a predictor only for T2-T3 but not T1-T2 transitions. This might be explained by the second follow-up showing somewhat less favorable results for occupational well-being and its development, possibly due to COVID-19. A supportive vs. unsupportive learning climate might have played a stronger role during the second period, as the necessity and value of a given resource can vary across contexts (Halbesleben et al., 2014). The capacity to manage resources, referring to one's ability to employ resources in handling work stress and excessive work demands, has been investigated in connection with well-being (Hochwarter et al., 2007). The availability of existing resources may be linked to how challenging it is to manage a new resource and thus how valuable it is to the employee (Halbesleben et al., 2014). This offers an intriguing perspective on why our findings on learning climate were not as widely supported as hypothesized. To operationalize the perceived learning climate, the environment may need to incorporate less overwhelming aspects, such as reduced intensification of work (Kubicek et al., 2015) or other crucial resources that may be scarce in today's working life.

Theoretical Contributions and Practical Implications

Our study contributes to the literature on the long-term development of employee well-being by applying a less-used person-centered approach. Studies utilizing developmental profiles have been conducted more often than transition analyses in occupational well-being research (Mäkikangas & Kinnunen, 2016). Our study also explored the hitherto less studied contextual factors in sustainable careers (De Vos et al., 2020; Van der Heijden et al., 2020). Our results support those of other studies on the changing nature of employee well-being that might be impacted, for example, by situational factors such as the availability of different resources.

Since employee well-being appears to be a dynamic concept and changes in situational factors are likely to impact it, striking a balance between increasing demands and organizational resources should be facilitated by leaders and human resource professionals to

minimize the long-term negative effects on employee well-being. While we may live in a world that values self-leadership and autonomy, employees could nevertheless benefit from help from their organization in prioritizing their learning efforts amid intensifying learning demands. This could not only ease an employee's overall burden but also ensure that organizational goals related to learning are met in the most effective way. Our results on learning climate are somewhat contradictory; hence to actualize the benefits of a supportive learning climate, we suggest having conversations with employees on what kind of learning-related support is perceived as helpful, as it might differ among units, teams, or individuals.

Limitations and Further Research

Our study has its limitations. First, we were unable to conduct a multilevel analysis by linking the participants to each other. Although occupational well-being and perceived learning climate can occur as an individual-level phenomenon, it might also be a shared phenomenon experienced within a specific team or a work community. If so, this would have added another layer to the findings. Second, complementing self-reports with other data collection methods such as interviews would have helped us to cover the studied aspects more thoroughly. Moreover, we would have gained more detailed information if we had included workaholism and job satisfaction in our profile analysis (based on the circumplex model of affective well-being; see Rantanen et al., 2023). Third, while we drew on the accelerated pace of life (Rosa, 2003, 2013) and work intensification (Kubicek et al., 2015) literatures, it would be beneficial to include measures of these using, for example, moderation analysis to study different conditions. At the same time it could also be examined how much value each individual accords the learning climate dimension (i.e., possible resource) in question, and whether this is reflected in the benefit that the individual gains from it.

With respect to the identified profiles, although their shapes remained similar at each measurement point, it would have added to the reliability of the results had we been able to set the means equal when studying the transitions between profiles. The study should be replicated with a larger sample: our findings on the perceived learning climate as a predictor of transitions from one profile to another were, in some cases, based on only a few people making the specific transition. In addition to using a person-centered perspective, the fact that we studied highly educated Finnish employees working as professionals and leaders means that our results are sample-specific. On average, our participants were rather experienced. It would be important to pay more attention to the career sustainability of younger and less experienced employees, as in addition to an increased risk for a premature retirement among white-collar workers in Finland, students, who are soon to enter working life– possibly the first time in their lives– were also at high risk for a premature retirement due to mental health disorders (Karolaakso et al., 2020).

Conclusion

This study addressed employee well-being development with the aim of promoting discussion on the contextual factors that have been less studied as resources in career sustainability among highly educated employees. The profile composition highlights the complexity of employee well-being, as individuals can experience positive and negative affect towards

their work simultaneously. Our results also show tentative evidence both for some aspects of perceived learning climate that could function as an organizational resource and for others that might be perceived as more stressful than helpful by employees, such as getting recognized by doing more. We need to bear in mind that resources are not necessarily universal, and their value can vary depending on the individual and the broader context. Overall, the three dimensions of perceived learning climate merit more longitudinal research to gain a profounder understanding of their impact on employee well-being and career sustainability.

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Author contributions KL designed the study, performed the statistical analyses, and drafted the manuscript. AT provided statistical consultation. JR and TF provided comments to the manuscript and were involved in the data collection. TF acted as a principal investigator (PI) in the study project. All authors contributed to the article and approved the submitted version.

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Data availability The datasets presented in this article are not readily available because anonymized data is not transferred outside the EU/EEA area. Requests to access the datasets should be directed to, taru.feldt@jyu.fi.

Declarations

Ethics statement Ethical review and approval were not required for the study on human participants in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

References

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling: A Multidisciplinary Journal*, *21*(3), 329–341. https://doi.org/10.1080/10705511.2014.915181

Auvinen, E., Huhtala, M., Kinnunen, U., Tsupari, H., & Feldt, T. (2020). Leader motivation as a building block for sustainable leader careers: The relationship between leadership motivation profiles and leader and follower outcomes. *Journal of Vocational Behavior*, *120*, 103428. https://doi.org/10.1016/j.jvb.2020.103428

Auvinen, E., Huhtala, M., Rantanen, J., & Feldt, T. (2021). Drivers or drifters? The who and why of leader role occupancy– A mixed-method study. *Frontiers in Psychology*, *12*. https://www.frontiersin.org/articles/https://doi.org/10.3389/fpsyg.2021.573924

Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. (2023). Job demands–resources theory: Ten years later. *Annual Review of Organizational Psychology and Organizational Behavior*, *10*, 25–53. https://doi.org/10.1146/annurev-orgpsych-120920-053933

Bakker, A. B., & Oerlemans, W. (2011). Subjective well-being in organization. In K. S. Cameron, & G. M. Spreitzer (Eds.), *The Oxford handbook of positive organizational scholarship* (pp. 178–189). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199734610.013.0014

Bereznowski, P., Atroszko, P. A., & Konarski, R. (2023). Work addiction, work engagement, job burnout, and perceived stress: A network analysis. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1130069

Collins, L. M., & Lanza, S. T. (2009). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences*. Wiley. https://doi.org/10.1002/9780470567333

De Vos, A., Van der Heijden, B., I. J., M., & Akkermans, J. (2020). Sustainable careers: Towards a conceptual model. *Journal of Vocational Behavior*, *117*, 103196. https://doi.org/10.1016/j.jvb.2018.06.011

Diallo, T. M. O., Morin, A. J. S., & Lu, H. (2016). Impact of misspecifications of the latent variance–covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling: A Multidisciplinary Journal*, *23*(4), 507–531. https://doi.org/10.1080/10705511.2016.1169188

Di Stefano, G., & Gaudiino, M. (2019). Workaholism and work engagement: How are they similar? How are they different? A systematic review and meta-analysis. *European Journal of Work and Organizational Psychology*, *28*(3), 329–347. https://doi.org/10.1080/1359432X.2019.1590337

Dyrbye, L. N., Thomas, M. R., Harper, W., Massie, F. S. Jr., Power, D. V., Eacker, A., Szydlo, D. W., Novotny, P. J., Sloan, J. A., & Shanafelt, T. D. (2009). The learning environment and medical student burnout: A multicentre study. *Medical Education*, *43*(3), 274–282. https://doi.org/10.1111/j.1365-2923.2008.03282.x

Eurofound. (2023). *Psychosocial risks to workers' well-being: Lessons from the COVID 19 pandemic*. Publications Office of the European Union. https://data.europa.eu/doi/10.2806/350964

Feldt, T., Rantanen, J., Hyvönen, K., Mäkikangas, A., Huhtala, M., Pihlajasaari, P., & Kinnunen, U. (2014). The 9-item bergen burnout inventory: Factorial validity across organizations and measurements of longitudinal data. *Industrial Health*, *52*(2), 102–112. https://doi.org/10.2486/indhealth.2013-0059

Ferguson, S. L., G. Moore, E. W., & Hull, D. M. (2020). Finding latent groups in observed data: A primer on latent profile analysis in Mplus for applied researchers. *International Journal of Behavioral Development*, *44*(5), 458–468. https://doi.org/10.1177/0165025419881721

Geurts, S. A. E., Beckers, D. G. J., & Tucker, P. (2013). Recovery from demanding work hours. In T. W. Taris, M. C. W. Peeters, & J. de Jonge (Eds.), *An Introduction to Contemporary Work Psychology* (pp. 196–219). Wiley. https://doi.org/10.1002/9781394259564.ch8

Gillet, N., Morin, A. J. S., Sandrin, E., & Houle, S. A. (2018). Investigating the combined effects of workaholism and work engagement: A substantive-methodological synergy of variable-centered and person-centered methodologies. *Journal of Vocational Behavior*, *109*, 54–77. https://doi.org/10.1016/j.jvb.2018.09.006

Halbesleben, J. R. B., Neveu, J.-P., Paustian-Underdahl, S. C., & Westman, M. (2014). Getting to the "COR": Understanding the role of resources in conservation of resources theory. *Journal of Management*, *40*(5), 1334–1364. https://doi.org/10.1177/0149206314527130

Harju, L. K., Seppälä, P., & Hakanen, J. J. (2023). Bored and exhausted? Profiles of boredom and exhaustion at work and the role of job stressors. *Journal of Vocational Behavior*, *144*, 103898. https://doi.org/10.1016/j.jvb.2023.103898

Hobfoll, S. (1989). Conservation of resources: A new attempt at conceptualizing stress. *The American Psychologist*, *44*, 513–524. https://doi.org/10.1037/0003-066X.44.3.513

Hobfoll, S. E. (2001). The influence of culture, community, and the nested-self in the stress process: Advancing conservation of resources theory. *Applied Psychology*, *50*(3), 337–421. https://doi.org/10.1111/1464-0597.00062

Hobfoll, S. E. (2011). Conservation of resource caravans and engaged settings. *Journal of Occupational and Organizational Psychology*, *84*(1), 116–122. https://doi.org/10.1111/j.2044-8325.2010.02016.x

Hobfoll, S. E., Halbesleben, J., Neveu, J. P., & Westman, M. (2018). Conservation of resources in the organizational context: The reality of resources and their consequences. *Annual Review of Organizational Psychology and Organizational Behavior*, *5*(1), 103–128. https://doi.org/10.1146/annurev-orgpsych-032117-104640

Hochwarter, W. A., Perrewé, P. L., Meurs, J. A., & Kacmar, C. (2007). The interactive effects of work-induced guilt and ability to manage resources on job and life satisfaction. *Journal of Occupational Health Psychology*, *12*(2), 125–135. https://doi.org/10.1037/1076-8998.12.2.125

Hollstein, B., & Rosa, H. (2023). Social acceleration: A challenge for companies? Insights for business ethics from resonance theory. *Journal of Business Ethics*, *188*(4), 709–723. https://doi.org/10.1007/s10551-023-05506-w

Kaltiainen, J., & Hakanen, J. (2022). Changes in occupational well-being during COVID-19: The impact of age, gender, education, living alone, and telework in a Finnish four-wave population sample. *Scandinavian Journal of Work Environment & Health*, *48*(6), 457–467. https://doi.org/10.5271/sjweh.4033

Kam, C., Morin, A. J. S., Meyer, J. P., & Topolnytsky, L. (2016). Are commitment profiles stable and predictable? A latent transition analysis. *Journal of Management*, *42*(6), 1462–1490. https://doi.org/10.1177/0149206313503010

Karolaakso, T., Autio, R., Näppilä, T., Nurmela, K., & Pirkola, S. (2020). Socioeconomic factors in disability retirement due to mental disorders in Finland. *European Journal of Public Health*, *30*(6), 1218–1224. https://doi.org/10.1093/eurpub/ckaa132

Kivimäki, M., Jokela, M., Nyberg, S. T., Singh-Manoux, A., Fransson, E. I., Alfredsson, L., Bjorner, J. B., Borritz, M., Burr, H., Casini, A., Clays, E., Bacquer, D. D., Dragano, N., Erbel, R., Geuskens, G. A., Hamer, M., Hooftman, W. E., Houtman, I. L., Jöckel, K. H., & Virtanen, M. (2015). Long working hours and risk of coronary heart disease and stroke: A systematic review and meta-analysis of published and unpublished data for 603 838 individuals. *The Lancet*, *386*(10005), 1739–1746. https://doi.org/10.1016/S0140-6736(15)60295-1

Kotera, Y., & Correa Vione, K. (2020). Psychological impacts of the new ways of working (NWW): A systematic review. *International Journal of Environmental Research and Public Health*, *17*(14). https://doi.org/10.3390/ijerph17145080

Kubicek, B., Paškvan, M., & Korunka, C. (2015). Development and validation of an instrument for assessing job demands arising from accelerated change: The intensification of job demands scale (IDS). *European Journal of Work and Organizational Psychology*, *24*(6), 898–913. https://doi.org/10.1080/1359432X.2014.979160

Lases, L. S. S., Arah, O. A., Busch, O. R. C., Heineman, M. J., & Lombarts, K. M. J. M. H. (2019). Learning climate positively influences residents' work-related well-being. *Advances in Health Sciences Education*, *24*(2), 317–330. https://doi.org/10.1007/s10459-018-9868-4

Lee, W. J. (Thomas), Sok, P., & Mao, S. (Eds.). (2022). When and why does competitive psychological climate affect employee engagement and burnout? *Journal of Vocational Behavior*, *139*, 1–16. https://doi.org/10.1016/j.jvb.2022.103810

Lehtiniemi, K., Tossavainen, A., Auvinen, E., Herttalampi, M., & Feldt, T. (2023). Do intensified job demands predict burnout? How motivation to lead and leadership status may have a moderating effect. *Frontiers in Psychology*, *14*. https://www.frontiersin.org/articles/https://doi.org/10.3389/fpsyg.2023.1048487

Lombardero-Posada, X. M., Murcia-Álvarez, E., Aguiar-Fernández, F. J., Méndez-Fernández, A. B., & González-Fernández, A. (2023). Burned out, engaged, both, or neither? Exploring engagement and burnout profiles among social workers in Spain. *Social Work*, *68*(2), 131–140. https://doi.org/10.1093/sw/swad002

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling: A Multidisciplinary Journal*, *16*(2), 191–225. https://doi.org/10.1080/10705510902751010

Martela, F., & Pessi, A. B. (2018). Significant Work Is About Self-Realization and Broader Purpose: Defining the Key Dimensions of Meaningful Work. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.00363

Maslach, C., Schaufeli, W. B., & Leiter, M. P. (2001). Job burnout. *Annual Review of Psychology*, *52*, 397–422. https://doi.org/10.1146/annurev.psych.52.1.397

Mauno, S., Feldt, T., Herttalampi, M., & Minkkinen, J. (2024). Are intensified job demands positive challenges for employees? Associations with work engagement in different occupational samples. *International Journal of Manpower*. https://doi.org/10.1108/IJM-09-2023-0537

Mäkikangas, A., & Kinnunen, U. (2016). The person-oriented approach to burnout: A systematic review. *Burnout Research*, *3*(1), 11–23. https://doi.org/10.1016/j.burn.2015.12.002

Mäkikangas, A., Kinnunen, U., Feldt, T., & Schaufeli, W. (2016a). The longitudinal development of employee well-being: A systematic review. *Work & Stress*, *30*(1), 46–70. https://doi.org/10.1080/02678373.2015.1126870

Mäkikangas, A., Rantanen, J., Bakker, A. B., Kinnunen, M. L., Pulkkinen, L., & Kokko, K., K. K (2015). The circumplex model of occupational well-being: Its relation with personality. *Journal for Person-Oriented Research*, *1*(3), 114–129. https://doi.org/10.17505/jpor.2015.13

Mäkikangas, A., Schaufeli, W., Leskinen, E., Kinnunen, U., Hyvönen, K., & Feldt, T. (2016b). Long-term development of employee well-being: A latent transition approach. *Journal of Happiness Studies*, *17*(6), 2325–2345. https://doi.org/10.1007/s10902-015-9696-7

Moeller, J., Ivcevic, Z., White, A. E., Menges, J. I., & Brackett, M. A. (2018). Highly engaged but burned out: Intra-individual profiles in the US workforce. *The Career Development International*, *23*(1), 86–105. https://doi.org/10.1108/CDI-12-2016-0215

Morin, A. J. S., & Litalien, D. (2019). Mixture modeling for lifespan developmental research. *Oxford Research Encyclopedia of Psychology*. Oxford University Press. https://doi.org/10.1093/acrefore/9780190236557.013.364

Muthén, L. K., & Muthén, B. O. (1998–2017). *Mplus User's Guide*. https://www.statmodel.com/download/usersguide/MplusUserGuideVer_8.pdf

Nikolova, I., Van Ruysseveldt, J., De Witte, H., & Van Dam, K. (2014). Learning climate scale: Construction, reliability and initial validity evidence. *Journal of Vocational Behavior*, *85*(3), 258–265. https://doi.org/10.1016/j.jvb.2014.07.007

Nikolova, I., Van Ruysseveldt, J., Van Dam, K., & De Witte, H. (2016). Learning climate and workplace learning: Does work restructuring make a difference? *Journal of Personnel Psychology*, *15*(2), 66–75. https://doi.org/10.1027/1866-5888/a000151

Obschonka, M., Silbereisen, R. K., & Wasilewski, J. (2012). Constellations of new demands concerning careers and jobs: Results from a two-country study on social and economic change. *Journal of Vocational Behavior*, *80*(1), 211–223. https://doi.org/10.1016/j.jvb.2011.08.002

Rantanen, J., Mäkikangas, A., Puukari, S., Koskela, S., Raudasoja, A., & Silvonen, J. (2023). Multifaceted investigation of occupational wellbeing profiles among guidance counsellors. *British Journal of Guidance & Counselling*, *52*(3), 546–563. https://doi.org/10.1080/03069885.2023.2247547

Rollero, C., Fedi, A., & De Piccoli, N. (2016). Gender or occupational status: What counts more for well-being at work? *Social Indicators Research*, *128*(2), 467–480. https://doi.org/10.1007/s11205-015-1039-x

Rosa, H. (2003). Social acceleration: Ethical and political consequences of a desynchronized high–speed society. *Constellations*, *10*(1), 3–33. https://doi.org/10.1111/1467-8675.00309

Rosa, H. (2013). *Social acceleration: A new theory of modernity*. Columbia University Press.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*(6), 1161–1178. https://doi.org/10.1037/h0077714

Salanova, M., Líbano, D., Llorens, M., S., & Schaufeli, W. B. (2014). Engaged, workaholic, burned-out or just 9-to-5? Toward a typology of employee well-being. *Stress and Health*, *30*(1), 71–81. https://doi.org/10.1002/smi.2499

Salmela-Aro, K., Hietajärvi, L., & Lonka, K. (2019). Work burnout and engagement profiles among teachers. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.02254

Salmela-Aro, K., Rantanen, J., Hyvönen, K., Tilleman, K., & Feldt, T. (2010). Bergen burnout inventory: Reliability and validity among finnish and estonian managers. *International Archives of Occupational and Environmental Health*, *84*, 635–645. https://doi.org/10.1007/s00420-010-0594-3

Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The measurement of work engagement with a short questionnaire: A cross-national study. *Educational and Psychological Measurement*, *66*(4), 701–716. https://doi.org/10.1177/0013164405282471

Schaufeli, W. B., Salanova, M., González-romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, *3*(1), 71–92. https://doi.org/10.1023/A:1015630930326

Seppälä, P., Mauno, S., Feldt, T., Hakanen, J., Kinnunen, U., Tolvanen, A., & Schaufeli, W. (2009). The construct validity of the Utrecht Work Engagement Scale: Multisample and longitudinal evidence. *Journal of Happiness Studies*, *10*(4), 459–481. https://doi.org/10.1007/s10902-008-9100-y

Szumilas, M. (2010). Explaining odds Ratios. *Journal of the Canadian Academy of Child and Adolescent Psychiatry*, *19*(3), 227–229. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2938757/

Taris, T. W., Schaufeli, W. B., & Shimazu, A. (2010). The push and pull of work: The differences between workaholism and work engagement. In A. B. Bakker, & M. P. Leiter (Eds.), *Work engagement a handbook of essential theory and research* (pp. 39–53). Taylor & Francis.

Van der Heijden, B., De Vos, A., Akkermans, J., Spurk, D., Semeijn, J., Van der Velde, M., & Fugate, M. (2020). Sustainable careers across the lifespan: Moving the field forward. *Journal of Vocational Behavior*, *117*, 103344. https://doi.org/10.1016/j.jvb.2019.103344

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, *18*(4), 450–469. https://doi.org/10.1093/pan/mpq025

Warr, P. (1990). The measurement of well-being and other aspects of mental health. *Journal of Occupational Psychology*, *63*(3), 193–210. https://doi.org/10.1111/j.2044-8325.1990.tb00521.x

Warr, P. (2007). *Work, happiness, and unhappiness*. Taylor & Francis.

Westman, M., Hobfoll, S., Chen, S., Davidson, O., & Laski, S. (2004). Organizational stress through the lens of conservation of resources (COR) theory. In P. L. Perrewe & D. C. Ganster (Eds.), *Interpersonal dynamics (research in occupational stress and well-being)* (Vol. 4, pp. 167–220). Emerald Group Publishing Limited.

Zacher, H., & Schmitt, A. (2016). Work characteristics and occupational well-being: The role of age. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.01411