Psychosocial Working Conditions among High-skilled Workers: A Latent Transition Analysis

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Abstract

Theories of psychosocial working conditions assume an interaction of different work environment characteristics. Most studies detail various aspects of such interactions, while fewer investigate the comprehensive patterns of interrelated variables. This exploratory study distinguishes patterns of psychosocial working conditions, describes their characteristics, and investigates their change over six years. The working conditions of 1,744 high-skilled workers in Sweden, of a representative sample of the working population, were empirically classified into four distinct patterns: 1) the Supporting pattern with a very low workload, very low time pressure, medium learning opportunities, high creativity requirements, and very high autonomy; 2) the Constraining pattern with a very low workload, very low time pressure, low learning opportunities, medium creativity requirements, and very low autonomy; 3) the Demanding pattern with a high workload, high time pressure, medium learning opportunities, high creativity requirements, and very low autonomy; 4) the Challenging pattern with a high workload, high time pressure, very high learning opportunities, very high creativity requirements, and very high autonomy. Importantly, these patterns were associated with significant differences in worker well-being. From an individual perspective, working conditions most often changed from patterns with a high workload and time pressure to patterns with lower levels of these demands. Over time, the prevalence of the Constraining pattern increased while that of the Challenging pattern decreased. To conclude, a person-centered approach broadens the understanding of the complex interplay between psychosocial working conditions and their longitudinal change, which can improve the tailoring of occupational health interventions.

Keywords: working conditions, person-centered, latent transition analysis, mixture modeling

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Introduction

Undoubtedly, working conditions are more favorable in some occupations than in others. High-skilled workers, defined as individuals having a highly specialized education and working with complex, non-routine tasks, typically hold occupations that include favorable characteristics, such as high earnings, good future prospects, good training opportunities, and high work autonomy (Eurofound, 2014a). Also, high-skilled workers consistently report better well-being and fewer health problems than mid- or low-skilled workers (Batinic, Selenko, Stiglbauer, & Paul, 2010; Eurofound, 2014a). However, in recent years, many managers, professionals, and technicians have experienced an intensification of psychosocial demands at work, which in turn increases the risk of exhaustion (Eurofound and EU-OSHA, 2014; Green, 2001; Kelliher & Anderson, 2010) and decreases job satisfaction (Lopes, Lagoa, & Calapez, 2014). To understand these seemingly contradicting phenomena, this paper applies the perspective of an individual to identify typical patterns of interrelations of working conditions and their prevalence within the large and expanding group of high-skilled workers.

To date, few studies have investigated the heterogeneity of the apparently privileged group of high-skilled workers. Yet, due to their occupational position or a given sector of work, it is likely that some high-skilled workers are more prone to report a certain pattern of working conditions. Moreover, the prevalence of specific patterns in the population of high-skilled workers may vary over time since individuals may have to, or actively seek to, transition between them. The broad and comprehensive methodology of this study, seldom used in previous research, makes important contributions to the existing knowledge by demonstrating how working conditions can be grouped into distinct patterns, how prevalent such patterns are among various groups of high-skilled workers, and how individuals transition between them over time. Going beyond current variable-oriented interaction frameworks, this study will contribute to opening up a discussion regarding the role of specific working conditions. Specifically, our approach allows for flexible modeling of complex patterns that extends the prevailing analysis of a number of two-way interactions. Grouping individuals into such complex patterns provides a unique opportunity for studying work environments and their change over time.

Studies employing person-centered approaches, clustering methods (Brusco, Steinley, Cradit, & Singh, 2012) and latent class procedures (Wang & Hanges, 2011), have become increasingly popular in organizational research (e.g., Bernhard-Oettel, Isaksson, & Bellaagh, 2008; Kam, Morin, Meyer, & Topolnytsky, 2013; Merecz & Andysz, 2014; Van den Broeck, Lens, De Witte, & Van Coillie, 2013). This study applies such a person-centered approach to identify patterns of individual experiences at work. While variable-centered approaches focus on associations between variables in a population, person-centered approaches use variability between individuals to distinguish unique subpopulations (e.g., Collins & Lanza, 2010; Wang & Hanges, 2011). For example, in this study, instead of describing relationships among variables representing job characteristics, we aim to distinguish a latent mixture of subpopulations characterized by different patterns of working conditions within a larger group of high-skilled workers. Such patterns provide an exploratory description of the interplay between different aspects of working conditions. Besides providing an empirical and exploratory distinction among the patterns, we aim to validate these patterns by investigating the stability of the classification over time along with the relationships of different patterns to worker well-being. Thus, another important contribution of this study lies in its identification of the ways that different patterns of working conditions relate to worker well-being.

Identifying patterns of psychosocial working conditions

Psychosocial factors at work refer to the way in which the work is organized, the content of the job, the workload, and working time arrangements (Eurofound and EU-OSHA, 2014). The main theories of psychosocial working conditions assume an interaction among various aspects of the work environment. For instance, different types of combinations have been identified based on the interrelations between job demands and different dimensions of job control, such as high-strain jobs characterized by high demands and low control, low strain jobs involving low demands and high control, and active-learning jobs with high demands and high control (Karasek, 1979; Karasek & Theorell, 1990). Others have investigated working conditions in which both job demands and job resources (including job control and other factors) are high, particularly when compared to conditions where demands are high but resources are low (Bakker, Hakanen, Demerouti, & Xanthopoulou, 2007; Bakker, van Veldhoven, & Xanthopoulou, 2010). Despite the many studies that have investigated the interaction effects of two or three types of job demands and job resources (e.g., Häusser, Mojzisch, Niesel, & Schulz-Hardt, 2010; Van Vegchel, De Jonge, & Landsbergis, 2005), research identifying complex multivariate patterns of psychosocial working conditions remains scarce. Specifically, this means that previous studies have mainly focused on investigating the degree to which a specific interaction of variables predicts various outcomes. In contrast, a person-centered methodology investigates how individuals differ in types that may incorporate the more complex interplay among the various aspects of a work environment. Consequently, such a person-centered approach allows for estimating the prevalence of each type (i.e., pattern) and for investigating changes among patterns over time. This important information is typically omitted in studies focusing on the strength of prediction rather than the prevalence of patterns of working conditions.

Only few studies have applied a person-centered approach. Yet, these studies have demonstrated that investigating unique combinations of several variables representing a pattern in working conditions can further knowledge beyond what is already known. Similarly to previous person-centered research, in this study indicators of psychosocial working conditions, such as time pressure or workload (typically referred to as job demands) and learning opportunities, creativity, and autonomy (often classified as job resources), are allowed to vary independently from one another and thus forming a unique pattern of working conditions. Previously, three types of such patterns have been distinguished: 1) healthy patterns characterized by high resources and low demands, 2) risky patterns with matching levels of resources and demands, and 3) unhealthy patterns characterized by low resources and high demands (Berntson, Wallin, & Härenstam, 2012; Härenstam et al., 2003; Vanroelen, Louckx, Moors, & Levecque, 2010). Typically, the healthy patterns are the most prevalent. Studying a full range of occupations, clusters of low-skilled workers have been found to differ from clusters of high-skilled workers. Specifically, the latter have been characterized by higher psychological demands, rather than physical demands, at work. These healthy, unhealthy, and risky patterns also emerged for the high-skilled group (Härenstam et al., 2003). In the current study, we expected to find a similar composition of at least three types of patterns, with healthy patterns being the most prevalent. However, the substantial heterogeneity of indicators, in addition to the diversity of workers in the samples of previous research, leads to a significant variability in the number and type of patterns identified. For example, together with dimensions of resources and demands respectively, previous studies have used different other indicators such as client conflicts and client recognition (Berntson, Wallin, & Härenstam, 2012), work-life balance (Härenstam et al., 2003), as well as overtime work and physical demands (Vanroelen, Louckx, Moors, & Levecque, 2010). The target population has also varied greatly. Some studies have included a very narrow sample (e.g., only managers in the public sector; Berntson, Wallin, & Härenstam, 2012) while others have studied a large group of workers from various occupations (Vanroelen, Louckx, Moors, & Levecque, 2010). Thus, the clusters identified in previous studies have been rather different from each other and difficult to compare systematically across samples. Also, the limited use of the person-centered approach in previous research makes it difficult to a priori define which and how many of the patterns of psychosocial working conditions to distinguish, particularly in the group of high-skilled workers. Thus, we adopted an exploratory study approach in which neither the number nor the prevalence of patterns was specified beforehand (Nylund-Gibson, Grimm, Quirk, & Furlong, 2014). To reflect typical aspects of the work environment, our choice of indicators was guided by the Job Demands-Control model (Karasek, 1979; Karasek & Theorell, 1990). The operationalization of this model includes the most parsimonious and commonly used set of indicators. Furthermore, these indicators can be combined in various ways in subpopulations of high-skilled workers. This means that the opportunity to make decisions concerning daily work, the work pace, the intensity of work, and requirements to be creative or to continuously learn new things may vary considerably among diverse occupational groups of highly-skilled professionals. To explore such variability, working conditions were not grouped in general terms of control and demands. Instead, they were investigated as separate indicators of unique work environment characteristics. Accordingly, we formulated the following research question:

Research Question 1: Which patterns of working conditions can be distinguished among high-skilled workers and how prevalent are these patterns?

Explaining differences in working conditions

Patterns of working conditions are likely to be associated with occupational differences among workers and as relating to an individual's occupational level and sector of work. However, these patterns also correspond to individual characteristics including gender and age. For instance, technicians and lower-level professionals typically have less decision autonomy regarding the ordering of both their job tasks and methods used (Eurofound, 2014a). As for managers, they seem to work more intensively, with demands being particularly high for women (Eurofound, 2014a; Gadinger et al., 2010). Not having enough time to get the job done also seems more prevalent among managers and technicians (Eurofound, 2012). Moreover, working conditions may vary considerably among different work sectors. For example, engineers more often encounter new processes and technologies (Eurofound, 2014b) and may thus have more learning opportunities at work than other high-skilled workers. Moreover, healthcare professionals tend to experience low levels of autonomy at work (e.g., Linzer, 2009; Lu, Barriball, & While, 2012), while education professionals often report a high workload (e.g., Ballet & Kelchtermans, 2009; Bauer et al., 2007). As for individual characteristics, women often report their work as more demanding (e.g., Theorell et al., 2014) and experience lower job control than men (e.g., Niedhammer, Sultan-Taïeb, Chastang, Vermeylen, & Parent-Thirion, 2012). In particular, women professionals report less decision autonomy and higher time pressure (Eurofound, 2012; Schütte, Chastang, Malard, Parent-Thirion, Vermeylen, & Niedhammer, 2014). Finally, older workers at the later stage of their careers often report having less stressful working conditions (Vanroelen et al., 2010). In general, younger workers are more likely to have jobs with multiple disadvantages, as compared to workers over 50 years of age (Eurofound, 2014a). Another factor involves workers gaining mastery and experience over time, which means that the older they get, the less complicated and demanding they may perceive their jobs. This perception relates to career development: over time, workers often reach a professional position involving lower demands (Eurofound, 2014a). In view of these findings, there is reason to believe that the patterns of working conditions will be linked to occupational differences and individual characteristics. However, since person-centered studies of working conditions are rare, we formulated a research question instead of a hypothesis:

> *Research Question 2*: Are certain groups of workers (managers, technicians, engineers, education professionals, healthcare professionals, women, older workers) more likely to have a specific pattern of working conditions?

Validating the patterns of working conditions

To ensure a meaningful interpretation of empirically identified patterns, we attempt to validate them with external variables (Bergman, Magnusson, & El-Khouri, 2003). Given the consistent findings showing that working conditions are linked to worker well-being and ill-being, this study included the validation variables of job satisfaction and emotional exhaustion. Job satisfaction scores reflect not only a pleasurable state resulting from the job but also relate to levels of positive affect and general life satisfaction (Bowling, Eschleman, & Wang, 2010; Connoll & Viswesvaran, 2000). Emotional exhaustion represents a key dimension of the burnout construct (Maslach & Leiter, 2008). Also, the emotional exhaustion subscale has been found to be the most robust and reliable dimension of burnout (Schaufeli & Enzmann, 1998). Moreover, recent findings suggest that exhaustion first occurs as an early symptom of burnout and then develops further in individuals with dysfunctional coping strategies (Gustavsson, Hallsten, & Rudman, 2010). Thus, the chosen variables represent important core constructs of well-being and ill-being, respectively.

According to the Job Demands-Control model (Karasek, 1979; Karasek & Theorell, 1990) and its extensions (the Job Demands-Control-Support model, Johnson & Hall, 1988; the Job Demands-Resources model, Demerouti, Bakker, Nachreiner, & Schaufeli, 2001), psychosocial working conditions relate to health and well-being in two primary ways. First, the so-called strain hypothesis assumes an increased likelihood of poor health and reduced well-being for individuals in highly demanding jobs (Häusser et al., 2010). Thus, individuals having to deal with high demands are expected to be more exhausted and less satisfied with their jobs than those with low demands. Specifically, the combination of high demands and low resources is expected to be the most detrimental to worker well-being (e.g., Härenstam et al., 2003; Lopes et al., 2014). Second, the so-called buffer hypothesis assumes that positive work characteristics attenuate the impact of high demands on worker well-being (Bakker, Demerouti, & Sanz-Vergel, 2014; van der Doef & Maes, 1999). This means that high demands, when combined with corresponding and sufficiently adequate resources, are considered neutral for well-being (Bakker et al., 2010; de Jonge & Dormann, 2006). Thus, in general, patterns with high intensity and a fast work pace, combined with opportunities to decide and learn, seem more likely to yield lower exhaustion and higher satisfaction than patterns that do not couple demanding aspects of work with such opportunities (Karasek & Theorell, 1990). For those with chronic exposure, the detrimental effects of stressors on well-being tend to accumulate over time (Ford, Matthews, Wooldridge, Mishra, Kakar, &

Strahan, 2014). Thus, one of the questions explored in this study investigates how different patterns relate to outcomes reflecting worker well-being over a two-year time lag.

Research Question 3: How do patterns of working conditions differ in terms of worker well-being after a two-year time lag?

Investigating changes over time

Variations in work characteristics are related to both organizational and individual factors. Negative aspects of the working environment, such as high job demands, seem to fluctuate more over time than positive aspects, such as job resources (Brauchli, Schaufeli, Jenny, Füllemann, & Bauer, 2013). Demands may also fluctuate as job requirements in project-based work vary (Pinto, Dawood, & Pinto, 2014) or change due to career transitions within organizations (Rigotti, Korek, & Otto, 2014). Also, individuals seem to modify independently their working conditions through job crafting (Tims, Bakker, & Derks, 2013). In particular, workers have been found to try to increase their job control and reduce organizational constraints (Li, Fay, Frese, Harms, & Gao, 2014). Thus, over time, the patterns of working conditions may undergo certain changes.

To date, no study has investigated whether and how the prevalence of patterns changes over time (structural stability) and whether and how workers transfer from one pattern to another (individual stability). The structural stability over time mainly contributes to the methodological validity of identified patterns, which confirms that the same patterns may be found at different time points (Bergman et al., 2003). However, it is even more interesting to investigate individual stability, which includes the prevalence and directions in which individuals transfer from one working condition pattern to another. Such an exploratory analysis of longitudinal transitions among the patterns of working conditions stands out as the main contribution of this study. We aim to explore whether individuals transfer between patterns, how common such transitions are, and whether the same types of transitions can be detected over the two-year periods between measurement occasions of this study.

Research Question 4: How do individuals transfer from one working conditions pattern to another over time?

Method

Participants and data collection

Participants came from the Swedish Longitudinal Occupational Survey of Health (SLOSH), a nationally representative longitudinal cohort survey (Magnusson Hanson, Theorell, Oxenstierna, Hyde, & Westerlund, 2008). Respondents recruited into SLOSH were originally drawn from the entire Swedish population after their stratification by county, citizenship, and inferred employment status. As part of the Swedish Work Environment Survey (SWES), a group of gainfully employed individuals, aged 16 to 64, were invited to respond to supplementary questionnaires (Magnusson Hanson, Chungkham, Ferrie, & Sverke, 2015). Through SLOSH, a successively increasing number of participants in SWES 2003-2011 who fulfilled the above criteria responded to self-report questionnaires in year 2008 (n = 11,441), 2010 (n = 11,525), and 2014 (n = 20,316). Ethical approval was obtained from the Swedish Central Ethical Review Board (Ref no #2014/2046-31).

The current analysis included a subsample (N = 1,744) of workers who fulfilled the three inclusion criteria: 1) responded to the SLOSH questionnaires in 2008, 2010, and 2012, 2) worked at least 30% of full-time during the past three months at all of the measurement occasions, and 3) were classified as high-skilled workers according to the Swedish Standard Classification of

Occupations (SSYK; Statistics Sweden, 2012). Regarding the last inclusion criterion, high-skilled workers were defined as those categorized into three occupational groups of the SSYK: 1) legislators, senior officials or managers, 2) professionals, and 3) technicians and associated professions. This classification was based on the job titles provided by the participants. The supplementary Table 1 presents detailed information about the representativeness of the analytic subsample. The general response pattern in the SLOSH panel involves more women, older, married or cohabiting, born in Sweden, with a university degree, and from the governmental sector responding to the questionnaire over time. These differences tend to become more substantial in later follow-ups; and so, we decided against modeling the data from the last wave. Thus, we only used well-being and ill-being scores from time 4 (2014) to represent differences in these measures over a two-year time lag.

At the baseline measurement in 2008, the mean age of participants was 47.4 (*SD* = 8.5), ranging from 25 to 65 years. The study sample included more women (60.8%) than men (39.2%). The majority of the participants were born in Sweden (93.9%), held a university degree (72.5%), were married or cohabitating (60.8%), and had children living at home (59.7%). Governmental institutions (57.7%) and private companies (37.6%) were primarily their employers. About half of the sample worked at enterprises employing fewer than 50 individuals (43.5%). The majority had a day job (87.4%) while others worked shifts (7.0%) or had non-regulated working hours (4.4%).

Measures

Psychosocial working conditions were measured with seven items based on the Swedish version of the Demand Control Questionnaire (Sanne, Torp, Mykletun, & Dahl, 2005). Indicators represented learning opportunities (“Do you have the opportunity to learn new things through your work?"); opportunities to be creative at work ("Does your work require creativity?"); decision autonomy ("Do you have a choice in deciding what you do at work?") and procedural autonomy ("Do you have a choice in deciding how you do your work?"); time pressure ("Do you have to work very fast?"); intensification of work ("Do you have to work very intensively?") and extensive workload ("Does your work demand too much effort?"). In the analysis, the items were treated as separate indicators meaning that no composite scales were formed. All items were rated on a 4-point response scale with alternatives labeled "yes, often", "yes, sometimes", "no, seldom", and "no, hardly ever." Answers of "yes, often" were coded as 1, while all other responses were coded as 0. This coding strategy was more likely to capture stable characteristics of the work environment rather than short-term fluctuations. In the analyses, a single binary indicator represented each item. Table 1 presents the prevalence of "yes, often" responses (coded "1").

Ill-being, in terms of emotional exhaustion, was measured with a two-year time lag. Five items were used in 2010 and 2012, while four items were used in 2014. Items used in 2010 and 2012 were excerpted from the Swedish version of the Maslach Burnout Inventory (Hallberg & Sverke, 2004), while the items used in 2014 were excerpted from the Shirom-Melamed Burnout Questionnaire (Grossi, Perski, Evengård, Blomkvist, & Orth-Gomér, 2003). These items (e.g., "My job makes me feel emotionally drained") were rated on a 6-point response format ranging from 1 "few times a year or never" to 6 "every day" (a 7-point scale was used in 2014). The scale yielded high internal consistency (α = .87 on average across time points) and moderate stability (r = .66 from 2010 to 2012, and r = .53 from 2012 to 2014). The mean index score from the scale was low (M = 2.22 [2010], 2.24 [2012], and 2.33 [2014], respectively). To simplify comparisons between groups, the index scores were standardized into a scale with M = 0 and SD = 1.

Well-being, in terms of job satisfaction, was also measured with a two-year time lag. A single-item indicator was used ("Roughly, how satisfied are you with your work?"). The response format ranged from 1 "very dissatisfied" to 8 "very satisfied." The stability of the score was moderate (r = .45 from 2010 to 2012 and r = .48 from 2012 to 2014). The mean score was high (M = 6.00 [2010], 6.09 [2012], and 6.04 [2014], respectively). Again, the scores were standardized into a scale with M = 0 and SD = 1 to simplify comparisons between groups.

Occupational position was coded according to the SSYK classification, and reflects the skill level of a worker based on the complexity of work tasks and the length of the formal education that is typical for the particular occupation (SSYK; Statistics Sweden, 2012). When comparing jobs, the jobs of technicians and associate professionals (e.g., dental hygienists) are considered less complex than are the jobs of professionals (e.g., dentists) and managers (e.g., managers in health care) within the same sector of work. Across the different time points, professionals formed the largest of the occupational groups (2008: 47.8%; 2010: 45.6%; 2012: 44.3%), followed by the group of technicians and associate professions (2008: 40.5%; 2010: 42.4%; 2012: 41.6%), while the minority group included managers and executives (2008: 11.8%; 2010: 11.9%; 2012: 14.1%). In the analysis, dummy variables were created for managers (1 = manager, 0 = not a manager) and technicians (1=technician, 0=not a technician), while professionals constituted the reference group.

The sector of work was coded according to the SSYK classification, and reflects the skill specialization of a worker based on the similarity of the required knowledge, tools, equipment, and product or service being typical for the occupation (SSYK; Statistics Sweden, 2012). The sample consisted of engineers and technical sciences professionals such as architects, analytical chemists, and statisticians (2008: 18.8%; 2010: 18.8%; 2012: 19.1%); healthcare professionals such as medical doctors, biologists, and pharmacologists (2008: 20.1%; 2010: 20.0%; 2012: 20.0%); education professionals such as teachers, lectures, and special education professionals (2008: 19.8%; 2010: 19.8%; 2012: 19.4%); and other professionals including business, art, and legal professionals (2008: 41.3%; 2010: 41.3%; 2012: 41.5%). In the analysis, dummy variables were created for engineers (1 = engineer, 0 = not an engineer), healthcare professionals (1 = healthcare professional, 0 = not a healthcare professional), and education professionals (1 = educational professional, 0 = not an educational professional), while other professionals constituted the reference group. The reference group included business professionals, legal professionals, archivists, librarians and related information professionals, social science and linguistics professionals, writers and creative or performing artists, religious professionals, and administrative professionals.

Analytic strategy

In this study, data were analyzed using latent class models, and their extensions, latent transition models, to estimate changes over time. Within this analytical approach, categorical latent variables are modeled to identify clusters of individuals who share a similar pattern of categorical indicators (for review see e.g., Collins & Lanza, 2010; Nylund, 2007). The analysis was divided into two main parts, following a classify-analyze strategy. First, we estimated the latent classes' measurement model (answering research question #1). Second, we validated the established latent classes by investigating the role of predictors of class membership (research question #2), testing differences between classes in terms of distal outcomes (research question #3), and estimating the longitudinal stability of classes and exploring transitions between classes over time (research question #4). The main advantage of the Latent Class Analysis (LCA) over traditional clustering methods (e.g., *k* means cluster analysis) is that the LCA estimates the uncertainty of a person's class membership, which can be referred to as measurement error (Wang & Hanges, 2011). To account for measurement error in class assignment, a three-step approach was implemented when estimating the effects of covariates and distal outcomes (Asparouhov & Muthén, 2014; Vermunt, 2010). First, we established an unconditional mixture model. Second, we classified participants according to their most probable latent class and estimated the measurement error of this assignment. Third, the latent classes were fixed at the values established for the time-invariant measurement model while taking into account the measurement error. This model was used to validate the latent classes by investigating their relationships with covariates and distal outcomes (i.e., auxiliary variables). Thus, the latent classes measurement model was treated as independent from its statistical relationship with both covariates and outcomes, which is a recommended solution in mixture modeling (Asparouhov & Muthén, 2014; Lanza, Tan, & Bray, 2013; Nylund-Gibson et al., 2014). Previous simulation analyses have confirmed that when classes are sufficiently well separated (i.e. entropy above 0.6), the three-step approach works as efficiently as the traditional one-step approach (Asparouhov & Muthén, 2014).

All the analyses were performed using Mplus 7.2. Missing data were handled by the full information maximum likelihood estimation (FIML) with standard errors and a chi-square test statistic robust to non-normality (MLR, see Muthén & Muthén, 1998-2012). The annotated Mplus code used to estimate all models is provided in the online supplementary material. All models were estimated with 700 random sets of start values to avoid the chance selection of a suboptimal solution (i.e., the local maxima problem; Hipp & Bauer, 2006). Model fit indicators included the

Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the sample-adjusted Bayesian information criterion (SABIC), with lower values indicating a better model fit for all indicators. BIC was used as the primary indicator, as previous simulation studies have identified BIC as the most accurate information criterion for determining the number of classes in mixture modeling (Nylund, Asparouhov, & Muthén, 2007). The entropy of the models was reported to describe the quality of the overall classification (Celeux & Soromenho, 1996). For model comparisons, the BIC difference was used with values higher than 10, providing strong evidence against the model with the higher BIC value (Kass & Raftery, 1995). Nested models were also compared with a chi-square difference test: the loglikelihood ratio test (LRT).

Results

Structure of the patterns

The number of classes was first determined in separate analyses within each point in time. Results of these cross-sectional latent class analyses are provided in the online supplementary material. Models with two to seven classes were tested. At all three points in time, the BIC increased significantly for the six-class solution, suggesting the five-class option fit the best. However, the drop of the BIC value from the four- to the five-class solution was minimal. An examination of item response probabilities revealed that the four-class solution was almost identical at each time point, while the five-class model varied significantly. A simultaneous analysis of the three points in time (see Table 2) confirmed that the four-class solution fit better than the five-class model (ΔBIC = 23.2). Thus, we decided to retain the more parsimonious four-class model, as it was supported both theoretically and empirically.

Next, we tested the stability of the latent class structure over time, i.e., the longitudinal measurement invariance. The invariant model assumes that the same number of classes is identified over time, and it constrains the thresholds (i.e., item-response probabilities) to equality for each indicator within each pattern over time. The same structure of classes over time is not a necessary requirement for LTA. Yet, in practice, holding the measurement invariant facilitates meaningful comparisons over time (Nylund, 2007). The nested models comparison suggested that the time-invariant measurement model was significantly different from the free model (LRT p = 0.005). However, the BIC value dropped significantly when reducing the number of parameters (ΔBIC = 330.2), indicating a better model fit of the time-invariant model. Also, the cross-sectional latent class analyses showed that the four classes were in fact very similar. Since an invariance of the measurement model would significantly simplify the overall model interpretation, we again decided to retain a more parsimonious model and held the measurement model as longitudinally invariant in subsequent analyses.

Characteristics of the patterns

Research Question 1: describing the patterns of psychosocial working conditions. Figure 1 shows the final item response probabilities for the four classes. A high probability of endorsing an item may be interpreted as high prevalence of a given characteristic of a work environment in a class. The working condition pattern characterized by a very low workload, a very low time pressure, medium learning opportunities, high creativity requirements, and a very high autonomy was labeled the “Supporting” class. On average, 38% of the sample was classified into this class and its prevalence was relatively stable over time. The working condition pattern involving a very low workload and a very low time pressure, but also low learning opportunities, medium creativity requirements, and a very low autonomy, was labeled the “Constraining” class. On average, 41% of the sample was classified into this class, and its prevalence increased over time. The working condition pattern with a high workload, a high time pressure, medium learning opportunities, high creativity requirements, but very low autonomy was labeled as the “Demanding” class. On average, 12% of the sample was classified into this class, and its prevalence was relatively stable over time. The working condition pattern with a high workload, a high time pressure, and very high learning opportunities, very high creativity requirements, and a very high autonomy was labeled the “Challenging” class. On average, 8% of the sample was classified into this class, and its prevalence was decreasing. Table 3 presents class membership as percentages of the sample.

Research Question 2: relating the patterns to worker characteristics. Covariates were added to the model to understand whether any particular group was more likely to have any specific psychosocial working conditions. First, we tested whether time-invariant covariates (gender, being older than 50 years of age at the baseline) and time varying covariates (occupational position, sector of work) had time-invariant effects. In other words, all covariates were expected to influence class membership in the same way at each point in time. A comparison between the models with all the covariates that had time-varying vs. time–invariant effects confirmed that the latter and the more parsimonious model fit the data equally well (LRT p = 0.29; ΔBIC = 150.7).

Next, we compared the effects of each of the four covariates (see Table 4). The null hypothesis was that the covariate of interest was not to contribute significantly to the classification (Collins & Lanza, 2010). In other words, when the null hypothesis is not rejected, workers are equally likely to be members of a certain class regardless of their gender, age, occupational position, and sector of work. Two covariates contributed to the classification above and beyond the other covariates: technician as occupational position (ΔBIC = 22) and education professional as sector of work

(ΔBIC = 13). In comparison to the professionals, the technicians were significantly less likely to be members of the Challenging class than all other classes. In comparison with other professions, education professionals were significantly more likely to be members of the Challenging class rather than the Constraining class or the Demanding class. Even though being a healthcare professional did not contribute significantly to the classification above and beyond other variables, the results suggest that healthcare professionals may be significantly more likely to be members of the Demanding class than of the Challenging class. Also, women were more likely to be members of the Demanding class rather than the Challenging class, but this result was not statistically significant (p = .52).

Research Question 3: relating the patterns to worker well-being. The patterns were also validated with two-year lagged outcomes (distal outcomes). Class membership at one time point (in 2008, 2010, and 2012) was used to estimate the level of work-related ill-being and well-being in terms of exhaustion and job satisfaction at the subsequent time point (in 2010, 2012, and 2014, respectively; see Table 5). Importantly, the comparison was conducted within a certain time point, namely two years after an individual was assigned to a pattern and regardless of possible transitions between patterns, which means regardless of any current classification.

As expected, membership in the Supporting class resulted in the lowest level of exhaustion two years later (lower than the sample mean), while membership in the Demanding class resulted in the highest level of exhaustion two years later (higher than the sample mean). Membership in the Constraining and the Challenging classes resulted in moderate levels of exhaustion (similar to the sample mean). Levels of job satisfaction were equally high for members of the Supporting and the Challenging classes (higher than the sample mean), moderate for members of the Constraining class (similar to the sample mean), and the lowest among members of the Demanding class (lower than the sample mean).

Research Question 4: describing longitudinal changes. Table 3 presents the probabilities of change between classes from time 1 to time 2 and from time 2 to time 3. The two sets of estimates were shown to be similar; the model assuming stationary transition probabilities fit the data equally well as did the free model (LRT $p = 0.43$; ΔBIC = 59.6). Thus, workers seem to have systematically changed class membership over time.

Membership in the Constraining and Supporting classes were fairly stable (82% to 92% of workers stayed in these classes over time), while membership in the Demanding and Challenging classes was rather unstable (37% to 58% of workers stayed in these classes over time). Typically, workers were moving out from the classes with a high workload, time pressure, and work intensity into classes with the lower levels of these demands; 32% to 39% moved from the Demanding to the Constraining class, and 37% to 40% moved from the Challenging to the Supporting class. One exception involved the transition between high demand classes, i.e., from the Challenging into the Demanding class for 11% to 18% of workers, which represents quite a substantial loss of decision autonomy and a moderate loss of learning opportunities and creativity requirements. Similarly, a transition between low demand classes - i.e., from the Supporting class into the Constraining class for 11% to 13% of workers - represented a sharp decrease in decision autonomy and a moderate loss in learning opportunities and creativity requirements. All transitions resulted in an increasing prevalence of the Constraining class, which at time 3 included almost half of the sample, and a decreasing prevalence of the Challenging class, which, at time 3, included only 5% of the sample.

Discussion

The results of this study provide a better understanding of what typical combinations of working conditions may look like, how prevalent they are among high-skilled workers, and what the different patterns mean for worker ill-being and well-being. The findings of this study may broaden existing knowledge about psychosocial working conditions in at least three ways. First, the findings revealed differences within a group of high-skilled workers, who previous studies have usually treated as a homogeneous group. Second, this study applied a person-centered approach, and thus modeled relationships between more complex patterns of working conditions than is possible within the prevailing interaction frameworks based on a variable-oriented approach. Third, the results provided evidence regarding the stability of working conditions patterns, as well as the likelihood of transitions between patterns over time.

The four patterns identified in this study were shown to be relatively stable over time, meaning that the same types of psychosocial working conditions were found across three time points. Specifically, the patterns showed configural (same number of the patterns), structural (invariant measurement of the patterns), predictive (time-invariant effects of the predictors), and explanatory (replicated relations between pattern membership and well-being outcomes) similarity (Morin, Meyer, Creusier, & Biétry, 2015). Yet, the prevalence of the patterns changed throughout the six-year study period. Over time, more workers reported lower creativity requirements, learning opportunities, and decision autonomy, as well as a lower workload and less time pressure at work. Psychosocial working conditions typically changed from patterns with a high workload and time pressure to patterns with low levels of such demands. However, workers also transferred from patterns with higher decision autonomy, learning opportunities, and creativity requirements to patterns with lower levels of these resources. Finding out that these two types of transitions are the most common opens up a new line of research. For instance, the transition from patterns with a high time pressure and a high workload to those with low levels may represent individual job crafting or career development. On the other hand, the transition into patterns with low decision autonomy may relate to organizational changes or fluctuations between different stages of various projects. Future studies are needed to specify and systematically test such transferring conditions, and to examine whether there are any differences between specific groups of workers (e.g., women, older workers).

The present study findings complement those of previous research, in particular studies explaining the characteristics of any interplay between variables (or indicators). Similar to the variable-centered approach, which is typically represented by regression methods, a person-centered analysis aims at capturing the interrelatedness among variables (Wang & Hanges, 2011). However, there are key differences between these approaches. Such differences correspond with the type of research questions asked. The identification of latent classes through response patterns assumes that the phenomenon in question is inherently categorical (e.g., a pattern of resources available at work), while regression analysis assumes that the phenomenon is continuous (e.g., the amount of resources available at work). The two methods may seem contradictory, but are in fact complementary and can also be used in the same analysis (e.g., growth mixture modeling; Muthén & Muthén, 2000). However, the person-centered approaches allow for complex multivariate interactions to be simply and implicitly modeled (Morin, Morizot, Boudrias, & Madore, 2011). Thus, the person-centered approaches seem to more adequately describe the complex reality of modern work, where ill-being and well-being outcomes are predicted by a set of patterned indicators rather than by a single factor.

Finally, the findings of this study bring a new perspective to existing theories of psychosocial working conditions. Current theoretical approaches focus largely on labeling certain job characteristics as supportive, for example job control (Häusser, Mojzisch, Niesel, & Schulz-Hardt, 2010) and job resources (Bakker, Demerouti, & Sanz-Vergel, 2014), or as detrimental to well-being, for example job demands or hindrance stressors (Crawford, Lepine, & Rich, 2010; Tuckey, Searle, Boyd, Winefield, & Winefield, 2015). Even though most theories assume that interactions between different psychosocial factors play a key role, such hypotheses usually specify a priori the factors that will act as demands and those that are to be considered resources. However, several studies have shown that a particular work environment characteristic may be positively or negatively related to well-being indicators depending on the specific context of a given work environment. For example, autonomy has been shown to have a curvilinear relationship to employee engagement (Kubicek, Korunka, & Tement, 2014), which suggests that an optimal level of autonomy may vary depending on the availability of other resources at work. Moreover, creativity requirements have been shown to be positively related to worker well-being when complemented by other matching work environment characteristics such as job complexity and autonomy (Shalley, Gilson, & Blum, 2000). Thus, we argue that integrating such variability into a theoretical framework explaining the role of different work environment characteristics requires a more complex and broader approach. Taken together, the findings of the present study suggest that a stable set of patterns may be a more adequate way of describing a work environment in its entirety. Using such patterns as predictors of worker well-being may further the knowledge regarding the complex interactions between work characteristics, and allow moving beyond the labeling of control and demands.

Limitations

Obviously, the present results are limited to the study group and setting, which includes highly skilled workers in Sweden. Overall, workers in Sweden have good working conditions, and the majority of establishments have developed sufficient procedures for how to deal with psychosocial risks at work (Eurofound and EU-OSHA, 2014). When it comes to worker characteristics, the employment rate of older workers in Sweden is very high compared to other European countries (OECD, 2013). Thus, the sample analyzed in this study was fairly old. For methodological reasons, only workers in gainful employment were included in the analytic sample. With long parental leaves (over 12 months) being common in Sweden, and particularly so among younger women, this selection strategy may have excluded some younger workers. Moreover, Sweden has a very protective employment law; thus, a vast majority of workers enjoy secure working contracts and permanent employment (e.g., Virtanen, Janlert, & Hammarström, 2011). Finally, attrition patterns typical for longitudinal panel studies may have affected the representativeness of the sample, especially in the later data collection occasions. (Supplementary Table 1 presents detailed information about the representativeness of the selected subsample.) These limitations mean that further validation studies are needed for a meaningful generalization of the study findings across diverse populations of high-skilled workers, but also to occupational groups in other cultural settings.

We decided to use mixture modeling to allow for a contextual and comprehensive analysis of psychosocial working conditions (Härenstam, 2009; Wang & Hanges, 2011). Yet, we did not account for qualitative differences within the group of highly skilled workers, such as job demands and job resources particularly salient for any specific occupation (e.g., Lone et al., 2014). While some job characteristics may be detrimental for worker well-being in one occupation, this may not be the case for another occupation (Sparks & Cooper, 1999). However, instead of splitting the sample into smaller occupational groups, we focused on the highly prevalent and rather general indicators of psychosocial working conditions that correspond well with the cognitively demanding characteristic of high-skilled work. A contextualized at an organizational level or arbitrarily defined sets of indicators used in previous person-centered studies (Berntson et al., 2012; Härenstam et al., 2003; Vanroelen et al., 2010) have hindered us to generalize and replicate their results. This means that we believe that the restricted and theory-guided set of indicators used in this study, which are available in many datasets, will enable confirmatory analyses of the patterns. Moreover, this will enable the testing of whether the patterns replicate in other samples of high-skilled workers and other occupational groups in other cultural contexts (Morin et al., 2015).

Additionally, we dichotomized the items included in the analyses to further simplify interpretation of the results. These methodological decisions may be regarded as limitations, since they may be considered as resulting in a restricted response range. This means that it may be argued that the four-point response scale, which participants used to rate the prevalence of indicators representing psychosocial working conditions, could be treated as continuous and thereby enable the use of latent profile analyses (LPA) instead of latent class analyses (LCA) (e.g., Collins & Lanza, 2010). However, treating a variable with a skewed distribution and only four categories as continuous raises concerns regarding the possible interpretation of a mean score (e.g., Speelman & McGann, 2013). In contrast, recoding one response alternative (in this study, “yes, often”) as a zero-one indicator of the occurrence of an event simplifies the interpretation of the latent patterns. Moreover, given that a number of indicators and response scales used to measure the job demands-control dimensions tend to vary across different studies and languages (Fransson et al., 2012), compared to a mean score in LPA, a threshold estimate obtained in LCA may be easier to replicate meaningfully in another sample when performing future confirmatory analyses. However, it should be acknowledged that the impact of such preliminary measurement decisions on later pattern structures remains unknown and has been acknowledged as difficult to estimate (Morin, Gagné, & Bujacz, 2016).

Practical implications and future directions

Modeling the complexity of psychosocial working conditions into four patterns may greatly simplify any diagnostic process. It can also help practitioners to quickly identify and distinguish between any healthy and risky patterns. Furthermore, our findings can be linked to previous research by using the label job resources for positive aspects of work environment and while denoting challenging working conditions as job demands. Applying this to the present findings, the description of the four patterns may be further simplified as follows: 1) the low demands-high resources pattern (Supporting), 2) the low demands-low resources pattern (Constraining), 3) the high demands-low resources pattern (Demanding), and 4) the high demands-high resources pattern (Challenging). Our study shows that these patterns are not equally prevalent in the sample of high-skilled workers. For example, the Challenging pattern that represents workers who deal with high demands at work seems to be quite rare (only 12% of the sample and decreasing over time). Thus, the strategy of balancing high demands with high resources (e.g., Bakker, van Veldhoven, & Xanthopoulou, 2010) only seems applicable in a limited number of situations.

The patterns and the typical directions of transitions may be used to plan targeted interventions. Instead of analyzing only the amount of positive and negative factors as experienced by workers within any work environment, the pattern approach focuses on the balance between different characteristics of the psychosocial work environment. Thus, the pattern-approach makes it easier to understand what any interrelations among work characteristics mean on an individual level. For example, the levels of exhaustion for the Constraining and Challenging patterns were shown to be similar, yet the reasons for their occurrence are different. In the Constraining pattern, workers may have limited decision autonomy and too few learning opportunities, while in the Challenging pattern they may experience an extensive workload and high time pressure. In view of this, different interventions - targeting different aspects of the psychosocial work environment and specifically focusing on different groups of individuals exhibiting different patterns - are likely to be needed for the two groups to decrease their ill-being and improve their well-being. Furthermore, some workers from the Challenging pattern may be at risk of losing decision autonomy, as they are likely to make a transition into the Demanding profile. Yet, a targeted intervention may prevent such a negative change.

Further studies are needed to explain why transitions in certain directions are more common than others. A further understanding of why changes occur would perhaps require an analysis including detailed information, not available here, on whether and how individuals craft their ways through their occupational careers. Also, the impact of societal and organizational changes should be included to determine the extent to which the transitions found are voluntary or involuntary and perhaps required because of societal change. Ideally, such research would also investigate whether transitions are related to life outside work (e.g., starting a family, parental leave, sickness absence) that may bring about changes in psychosocial working conditions among high-skilled workers.

Such a holistic approach combining work and non-work factors would provide an in-depth understanding of how high-skilled workers adapt to change throughout their lives.

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Table 1

Study Variables and Correlations within Time Points (N = 1744)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Gender (*1=female, 0=male*)	**-.12**	.01	**-.32**	**.23**	**.20**	**.07**	.03	.00	-.01	**.07**	**.05**	**.05**	**.12**	.01
Age	.02	**-.07**	**-.14**	**.07**	**.07**	**-.10**	.02	**.07**	**.11**	-.01	.04	**.06**	-.01	.04
Time 1 (2008)														
1. Managers	*.12*													
2. Technicians	**-.30**	.40												
3. Engineers	**-.07**	**.05**	*.19*											
4. Healthcare professionals	**-.10**	.04	**-.24**	*.20*										
5. Education professionals	**-.07**	**-.09**	**-.24**	**-.25**	*.20*									
6. Learning opportunities	.04	**-.07**	.03	.02	**-.07**	*.52*								
7. Creativity requirement	-.03	**-.08**	-.02	**-.08**	**.27**	**.18**	*.67*							
8. Freedom how to work	**.10**	**-.11**	-.01	**-.10**	**.14**	**.07**	**.14**	*.61*						
9. Freedom what to do	**.10**	-.04	**-.07**	**-.09**	**.11**	**.09**	**.15**	**.46**	*.29*					
10. Working fast	**.06**	-.02	**-.09**	**.07**	**-.06**	**.07**	.05	**-.11**	**-.06**	*.24*				
11. Working intensively	**.08**	**-.12**	**-.08**	.02	.02	**.08**	**.09**	-.04	-.03	**.52**	*.21*			
12. Working with too much effort	**.08**	**-.08**	**-.10**	.01	**.11**	.03	**.14**	-.04	-.04	**.31**	**.45**	*.22*		
Time 2 (2010)														
1. Managers	*.12*													
2. Technicians	**-.32**	*.42*												
3. Engineers	**-.05**	.02	*.19*											
4. Healthcare professionals	**-.07**	**.09**	**-.24**	*.20*										
5. Education professionals	**-.07**	**-.12**	**-.24**	**-.25**	*.20*									
6. Learning opportunities	.00	**-.08**	.00	.00	-.03	*.50*								
7. Creativity requirement	.00	**-.08**	-.03	**-.07**	**.23**	**.21**	*.67*							

8. Freedom how to work	**.08**	**-.13**	.00	**-.09**	**.10**	**.12**	**.16**	*.56*						
9. Freedom what to do	**.08**	**-.05**	**-.07**	**-.04**	**.08**	.04	**.14**	**.49**	*.28*					
10. Working fast	.03	-.03	**-.05**	**.07**	-.02	**.08**	**.07**	-.04	-.02	*.17*				
11. Working intensively	**.07**	**-.07**	**-.06**	.02	**.05**	**.09**	**.08**	-.04	-.02	**.49**	*.14*			
12. Working with too much effort	**.07**	**-.08**	**-.08**	.00	**.14**	.04	**.09**	-.01	.00	**.32**	**.43**	*.15*		
13. Emotional exhaustion	**-.05**	**-.06**	**-.09**	.03	**.15**	-.04	**.07**	**-.14**	**-.14**	**.23**	**.24**	**.27**	*2.2*	
14. Job satisfaction	**.12**	-.03	-.01	.02	**-.07**	**.14**	-.01	**.19**	**.16**	**-.06**	**-.07**	**-.14**	**-.43**	*6.0*
Time 3 (2012)														
1. Managers	*.14*													
2. Technicians	**-.34**	*.42*												
3. Engineers	**-.09**	**.07**	*.19*											
4. Healthcare professionals	**-.05**	**.07**	**-.24**	*.20*										
5. Education professionals	**-.09**	**-.09**	**-.24**	**-.25**	*.19*									
6. Learning opportunities	.01	**-.08**	.03	.00	.01	*.41*								
7. Creativity requirement	-.03	**-.07**	-.03	**-.07**	**.25**	**.22**	*.65*							
8. Freedom how to work	**.09**	**-.13**	-.04	**-.08**	**.09**	**.13**	**.14**	*.54*						
9. Freedom what to do	**.07**	-.04	**-.06**	**-.05**	.02	**.12**	**.12**	**.48**	*.27*					
10. Working fast	.03	-.02	**-.08**	**.07**	-.02	-.01	**.07**	**-.08**	-.05	*.16*				
11. Working intensively	**.08**	**-.09**	**-.07**	.03	.03	**.06**	**.08**	-.03	.01	**.49**	*.11*			
12. Working with too much effort	**.06**	**-.09**	**-.09**	-.02	**.17**	**.05**	**.13**	**-.06**	**-.05**	**.35**	**.45**	*.15*		
13. Emotional exhaustion	-.02	**-.07**	**-.06**	.03	**.15**	-.02	**.11**	**-.17**	**-.15**	**.22**	**.21**	**.31**	*2.2*	
14. Job satisfaction	**.08**	-.04	-.03	.04	**-.09**	**.16**	-.01	**.23**	**.19**	**-.09**	**-.08**	**-.15**	**-.48**	*6.1*

Note. Psychological working conditions are coded 1= "*yes, often*" and 0= "*yes, sometimes*", "*no, seldom*" or "*no, hardly ever*". Prevalence in percentage of the response coded as "1" is presented in italics in the diagonal. Means are presented in italics in diagonal. For the occupational position comparisons, professionals are the reference group. For the sector of work comparisons, other professionals are the reference group. Significant correlations marked with bold, p <.05.

Table 2

Comparison of Measurement Models in Latent Transition Analyses

k	LL	SCF	#fp	AIC	BIC	SABIC	Entropy
2	-19683.34	1.04	45.00	39456.67	39702.55	39559.59	0.82
3	-18964.46	1.04	69.00	38066.91	38443.92	38224.72	0.73
4	-18816.31	1.09	93.00	37818.63	38326.78	38031.33	0.75
5	-18738.37	1.11	117.00	37710.73	38350.01	37978.32	0.75
6	-18697.33	1.05	141.00	37676.66	38447.08	37999.13	0.75
Final measurement model invariant across time points							
4	-18860.21	1.21	37.00	37794.43	37996.59	37879.05	0.73

Note: k = number of latent classes in the model; LL = model log likelihood; SCF = scaling correction factor of the robust maximum likelihood estimator (MLR); #fp = number of free parameters; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = sample- adjusted BIC.

Table 3

Class Membership and Transition Probabilities

	Supporting (1)	Constraining (2)	Demanding (3)	Challenging (4)
Class membership based on the most likely latent pattern				
Time 1	0.37	0.34	0.16	0.12
Time 2	0.39	0.42	0.10	0.08
Time 3	0.37	0.48	0.10	0.05
Transition probabilities from Time 1 classes (rows) to Time 2 classes (columns)				
Supporting (1)	**0.84**	0.11	0.01	0.04
Constraining (2)	0.05	**0.92**	0.03	0.01
Demanding (3)	0.07	0.39	**0.47**	0.07
Challenging (4)	0.40	0.07	0.11	**0.41**
Transition probabilities from Time 2 classes (rows) to Time 3 classes (columns)				
Supporting (1)	**0.82**	0.13	0.02	0.04
Constraining (2)	0.04	**0.92**	0.04	0.00
Demanding (3)	0.05	0.32	**0.58**	0.05
Challenging (4)	0.37	0.08	0.18	**0.37**

Note. Probabilities of staying in the same class are marked in bold.

Table 4

Predictors of Class Membership

	Supporting (1)		Constraining (2)		Demanding (3)	
	logit	*OR*	logit	*OR*	Logit	*OR*
Gender	-0.15	*0.86*	-0.09	*0.91*	0.39	*1.48*
Age	0.10	*1.10*	-0.21	*0.81*	-0.10	*0.90*
Technicians	0.84***	*2.31*	1.09***	*2.97*	0.81***	*2.26*
Managers	-0.16	*0.85*	-0.76***	*0.46*	-0.18	*0.84*
Engineers	0.12	*1.12*	0.35	*1.42*	-0.22	*0.80*
Healthcare professionals	0.20	*1.22*	0.38	*1.47*	0.56*	*1.75*
Education professionals	-0.06	*0.94*	-0.85***	*0.43*	-0.45*	*0.64*

Note. OR = Odds Ratio. Gender is coded 1 = female and 0 = male. Age is coded 1 = older than 50 years and 0 = younger than 50 years. Challenging (4) class was selected as the reference. For the occupational position comparisons, professionals are the reference group. For the sector of work comparisons, other professionals are the reference group * $p< .05$; ** $p< .01$; *** $p < .001$

Table 5

Lagged Effects of Class Membership on Well-being

	Supporting (1)	Constraining (2)	Demanding (3)	Challenging (4)
Time 1 classes → Time 2 outcomes				
Exhaustion	-0.77	0.04 [a]	0.97	0.28 [a]
Job satisfaction	0.47 [a]	-0.27	-0.67	0.41 [a]
Time 2 classes → Time 3 outcomes				
Exhaustion	-0.67	0.10 [a]	1.11	0.47 [a]
Job satisfaction	0.48 [a]	-0.28	-0.76	0.46 [a]
Time 3 classes → Time 4 outcomes				
Exhaustion	-0.67	0.18	0.71 [a]	0.68 [a]
Job satisfaction	0.47 [a]	-0.24	-0.61	0.22 [a]

Note. Values above zero represent scores higher than the sample mean; values below zero represent scores lower than the sample mean. Values marked with the same superscript letter are similar within each row. All other values are significantly different from one another ($p < .05$).

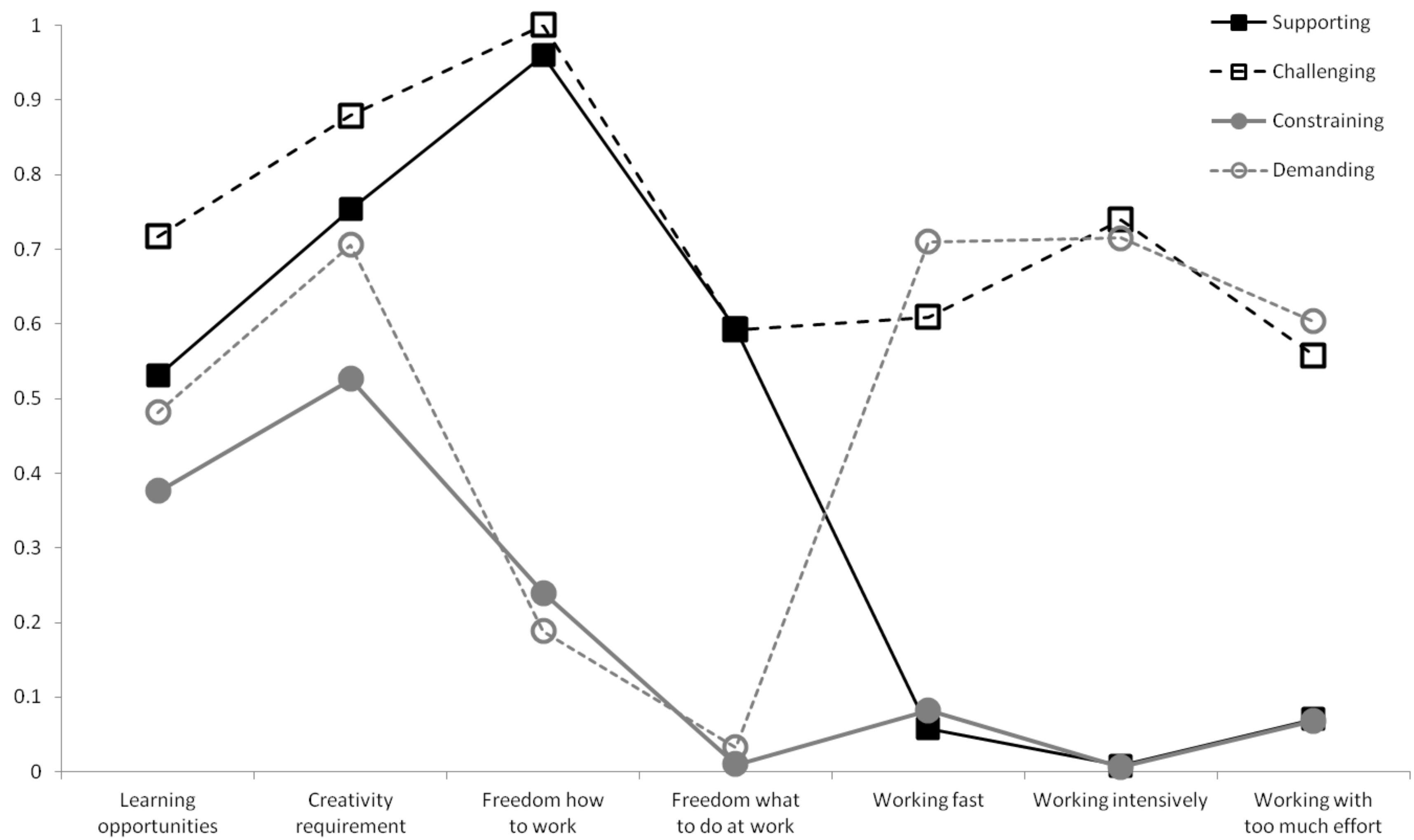

Figure 1. Patterns of item response probabilities for the four classes.

Supplementary Material

1) Representativeness of the analytic sample
2) Cross-sectional latent class analyses
3) Mplus input code to estimate the latent class analysis model
4) Mplus input code to estimate the latent transition analysis model
5) Mplus input code to estimate the latent transition analysis model with measurement invariance across time points
6) Mplus input code for the three-step procedure to account for measurement error using classify-analyze strategy
7) Mplus input code to estimate the autoregressive latent transition analysis model with stationary transition probabilities
8) Mplus input code to estimate the autoregressive latent transition analysis model with covariates
9) Mplus input code to estimate the autoregressive latent transition analysis model with distal outcomes

1) Representativeness of the analytic sample

Supplementary Table 1

Comparison between Analytic Sample and Full Sample of High-Skilled Workers

2008	Analytic Sample (*N* = *1744*)			Full Sample (*N* = *5955*)			
	Mean (SD)	*n*	% valid	Mean (SD)	*n*	% valid	*p*
Age	47.36 (8.55)			49.27 (11.27)			*<.01*
Women		1060	60.8		3318	55.7	*<.01*
Managers		205	11.8		802	13.5	*.06*
Technicians		706	40.5		2591	43.5	*.02*
Born in Sweden		1635	93.9		5617	94.4	*.33*
University degree		1263	72.5		3718	62.5	*<.01*
Married or cohabitating		1061	60.8		3561	59.8	*.44*
Children living at home		1035	57.9		2825	47.9	*<.01*
Employed by government		967	57.7		2549	49.9	*<.01*
Employed by private		631	37.6		2092	41.0	*.42*
Small enterprises		731	43.5		2470	48.2	*.74*
Day job		1502	87.4		5012	85.6	*.05*
Shift work		121	7.0		386	6.6	*.50*
Non-regulated work hours		75	4.4		309	5.3	*.13*
Working conditions							
Learning opportunities	1.53 (0.59)	901	57.7	1.58 (.62)	2870	48.5	*<.01*
Creativity requirement	1.36 (0.56)	1174	67.4	1.40 (.58)	3836	64.9	*.01*
Freedom how to work	1.45 (0.61)	1054	60.6	1.47 (.64)	3550	60.1	*.23*
Freedom what to do	1.96 (0.77)	505	29.0	1.93 (.80)	1946	32.9	*.16*
Working fast	1.94 (0.68)	425	24.4	1.96 (.70)	1424	24.1	*.28*
Working intensively	2.14 (0.81)	371	21.4	2.12 (.80)	1260	21.4	*.36*
Working with too much effort	2.07 (0.74)	396	21.9	2.09 (.76)	1147	22.3	*.32*

Note: Sample selected for this study included high-skilled workers who were gainfully employed and completed the questionnaire at all the measurement occasions. Small enterprises were defined as those employing fewer than 50 individuals. Psychological working conditions were coded *1= "yes, often"*, 2= *"yes, sometimes", 3="no, seldom" or 4="no, hardly ever"*. The figures present the prevalence in percentage of the response coded as "1".

2) Cross-sectional latent class analyses

The analysis of a latent mixture reveals diversity within a population. The number of possible subpopulations is finite, and some patterns will typically occur more often than others (Bergman, & Magnusson, 1997; Foti, Thompson, & Allgood, 2011). This unobserved heterogeneity can be identified and modeled through mixture models, such as Latent Class Analysis, LCA (e.g., McLachlan & Peel, 2000; Nylund-Gibson et al., 2014). LCA identifies subtypes of individuals who exhibit similar patterns of certain characteristics (Collins & Lanza, 2010; Wang & Hanges, 2011) meaning that individuals classified together have a similar pattern of responses to a set of questions representing individual characteristics.

The goal of cross-sectional analyses was twofold: 1) to examine how many groups with distinguished working conditions (classes) that emerge at each time point, and 2) to examine the similarity of the structure of the classes across time points. Thus, this preliminary analysis allowed us to test whether the class structure would replicate across three time points.

All the analyses were performed with Mplus 7.11 using the same specification and model fit indices as in the main analyses (Latent Transition Analyses). The Bootstrapped Likelihood Ratio Test (BLRT) was only used in cross-sectional analyses as it is unavailable for models with more than one categorical latent variable (Muthén and Muthén, 1998-2012). The BLRT compares a *k* class model with a *k-1* class model, with a significant *p* value indicating that a model with less latent classes should be rejected in favor of a model with more latent classes (Nylund, Asparouhov, & Muthén, 2007).

The Supplementary Table 2 present results of the cross-sectional latent class analyses. According to the BLRT, a six-class solution had the best fit at times 1 and 3, while a five-class solution had the best fit at time 2. However, the six-class solution suffered from estimation problems at time 2 and resulted in small classes (only 1.8% prevalence) at time 1. The drop in BIC value flattened out already around four classes. The change from the four to the five-class model resulted in a significant increase in BIC value at time 1 (ΔBIC = 23.4), an insignificant increase at time 2 (ΔBIC = 1.5), and an insignificant decrease at time 3 (ΔBIC = 3.6). Thus, the BIC value provided strong support for the four-class model at time 1, and no evidence of the four-class model being worse than the five-class model at times 2 and 3.

The structure of the four-class solution at each point in time is presented in the Supplementary Figure 1. The estimated classes were very similar across time points. The same four-class structure was replicated in the longitudinal model reported in the main manuscript.

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Supplementary Table 2

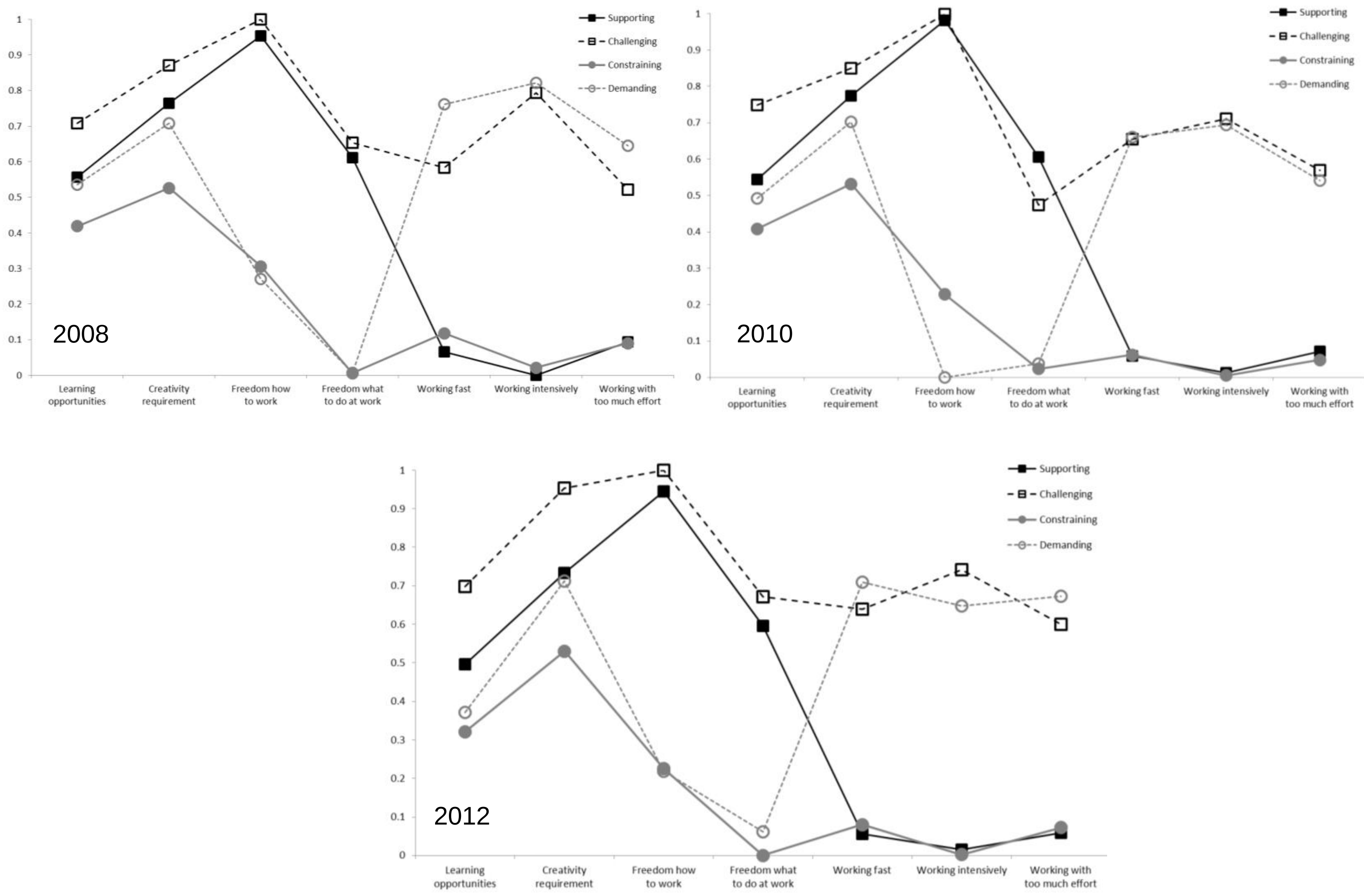
Model Comparison in Cross-Sectional Latent Class Analyses

k	BLRT	LL	SCF	#fp	AIC	BIC	SABIC	Entropy
Time 1 (2008)								
2	<.000	-6885.59	1.03	15	13801.17	13883.12	13835.47	0.80
3	<.000	-6677.15	1.05	23	13400.29	13525.95	13452.88	0.71
4	<.000	-6607.68	1.03	31	13277.36	13446.73	13348.24	0.73
5	<.000	-6589.55	1.05	39	13257.09	13470.16	13346.26	0.75
6	<.000	-6575.80	1.08	47	13245.61	13502.38	13353.07	0.78
7	0.092	-6565.45	1.03	55	13240.90	13541.39	13366.66	0.80
Time 2 (2010)								
2	<.000	-6446.73	1.03	15	12923.46	13005.41	12957.76	0.81
3	<.000	-6194.42	1.03	23	12434.83	12560.49	12487.42	0.74
4	<.000	-6148.52	1.06	31	12359.05	12528.41	12429.93	0.77
5	<.000	-6119.40	1.01	39	12316.81	12529.88	12405.98	0.78
6	0.208	-6110.32	1.05	47	12314.65	12571.43	12422.11	0.74
7	0.999	-6105.00	1.04	55	12320.01	12620.49	12445.76	0.75
Time 3 (2012)								
2	<.000	-6341.11	1.05	15	12712.22	12794.17	12746.51	0.84
3	<.000	-6083.22	1.04	23	12212.45	12338.10	12265.03	0.73
4	<.000	-6050.48	1.19	31	12162.96	12332.33	12233.84	0.75
5	<.000	-6018.85	1.27	39	12115.70	12328.77	12204.87	0.71
6	<.000	-6000.55	1.04	47	12095.10	12351.88	12202.57	0.73
7	0.182	-5992.27	1.11	55	12094.54	12395.02	12220.29	0.74

Note: k = number of latent classes in the model; BLRT = *p* value of the parametric bootstrapped likelihood ratio test for *k*-1 vs. *k* classes; LL = model log likelihood; SCF = scaling correction factor of the robust maximum likelihood estimator. #fp = number of free parameters; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = sample-adjusted BIC.

Supplementary Figure 1

Item-Response Probabilities for the Four Classes in the Cross-Sectional Latent Class Analyses



3) Mplus input code to estimate the latent class analysis model

```
TITLE: Cross-sectional Latent Class Analyses
DATA: FILE = data.dat;
VARIABLE:   NAMES =
!binary indicators of demands-resources at time 1
t1learn t1crdem t1how t1what t1fast t1hard t1effort
!binary indicators of demands-resources at time 2
t2learn t2crdem t2how t2what t2fast t2hard t2effort
!binary indicators of demands-resources at time 3
t3learn t3crdem t3how t3what t3fast t3hard t3effort
!covariates and outcomes were not be used at this stage of the analyses
t1gender t1age t1exe t1tech t2exe t2tech t3exe t3tech
t2ssat t2sburn t3sburn t3ssat t4sburn t4ssat;
MISSING are all (-9); !defines missing values coding
USEVARIABLES ARE !list of variables for the analysis at time 1
t1learn t1crdem t1how t1what t1fast t1hard t1effort;
CATEGORICAL = all; !specifies all used variables as categorical
CLASSES = c (4); !defines a categorical latent variable c with 4 latent classes
ANALYSIS:
TYPE = MIXTURE; !defines mixture modelling
PROCESSORS IS 4; !defines nb of threads to speed up the analysis
STARTS 700 100; !increases the default nb of initial random starts to 700
!and asks for 100 to be retained for final optimization
LRTSTARTS (0 0 100 40); !defines a number of iterations for the BLRT
PLOT:
type is plot2; !request item probabilities plot to reveal a class structure
series is t1learn (1) t1crdem (2) t1how (3)
t1what (4) t1fast (5) t1hard (6) t1effort (7);
OUTPUT:
tech14; !request the results of the BLRT
```

4) Mplus input code to estimate the latent transition analysis model

TITLE: Latent Transition Analysis
DATA: FILE = data.dat;
[VARIABLE command is specified in the same way as in the cross-sectional analyses; demands-resources indicators from all three data points are used]
CLASSES = c1 (4) c1 (4) c3 (4); *!defines three categorical latent variables*
!for three time points respectively with 4 classes each
[ANALYSIS command is specified in the same way as in the cross-sectional analyses]
MODEL:
%OVERALL%
MODEL C1: *!specifies the model at time 1*
%C1#1%
[t1learn$1] ; [t1crdem$1] ; [t1how$1] ; [t1what$1]; [t1hard$1] ; [t1fast$1] ; [t1effort$1];
%C1#2%
[t1learn$1] ; [t1crdem$1] ; [t1how$1] ; [t1what$1]; [t1hard$1] ; [t1fast$1] ; [t1effort$1];
%C1#3%
[t1learn$1] ; [t1crdem$1] ; [t1how$1] ; [t1what$1]; [t1hard$1] ; [t1fast$1] ; [t1effort$1];
%C1#4%
[t1learn$1] ; [t1crdem$1] ; [t1how$1] ; [t1what$1]; [t1hard$1] ; [t1fast$1] ; [t1effort$1];
MODEL C2: *!specifies the model at time 2*
%C2#1%
[t2learn$1] ; [t2crdem$1] ; [t2how$1] ; [t2what$1]; [t2hard$1] ; [t2fast$1] ; [t2effort$1];
%C2#2%
[t2learn$1] ; [t2crdem$1] ; [t2how$1] ; [t2what$1]; [t2hard$1] ; [t2fast$1] ; [t2effort$1];
%C2#3%
[t2learn$1] ; [t2crdem$1] ; [t2how$1] ; [t2what$1]; [t2hard$1] ; [t2fast$1] ; [t2effort$1];
%C2#4%
[t2learn$1] ; [t2crdem$1] ; [t2how$1] ; [t2what$1]; [t2hard$1] ; [t2fast$1] ; [t2effort$1];
MODEL C3: *!specifies the model at time 3*
%C3#1%
[t3learn$1] ; [t3crdem$1] ; [t3how$1] ; [t3what$1]; [t3hard$1] ; [t3fast$1] ; [t3effort$1];
%C3#2%
[t3learn$1] ; [t3crdem$1] ; [t3how$1] ; [t3what$1]; [t3hard$1] ; [t3fast$1] ; [t3effort$1];
%C3#3%
[t3learn$1] ; [t3crdem$1] ; [t3how$1] ; [t3what$1]; [t3hard$1] ; [t3fast$1] ; [t3effort$1];
%C3#4%
[t3learn$1] ; [t3crdem$1] ; [t3how$1] ; [t3what$1]; [t3hard$1] ; [t3fast$1] ; [t3effort$1];

5) **Mplus input code to estimate the latent transition analysis model with measurement invariance across time points**

TITLE: Latent Transition Analysis
DATA: FILE = data.dat;
[VARIABLE and ANALYSIS commands are specified as before]
MODEL:
%OVERALL%
MODEL C1: *!specifies the model at time 1 with constraints on thresholds*
%C1#1%
[t1learn$1] (11) ; [t1crdem$1] (12); [t1how$1] (13); [t1what$1] (14); [t1hard$1] (15) ; [t1fast$1] (16); [t1effort$1] (17);
%C1#2%
[t1learn$1] (21) ; [t1crdem$1] (22); [t1how$1] (23); [t1what$1] (24); [t1hard$1] (25) ; [t1fast$1] (26); [t1effort$1] (27);
%C1#3%
[t1learn$1] (31) ; [t1crdem$1] (32); [t1how$1] (33); [t1what$1] (34); [t1hard$1] (35) ; [t1fast$1] (36); [t1effort$1] (37);
%C1#4%
[t1learn$1] (41) ; [t1crdem$1] (42); [t1how$1] (43); [t1what$1] (44); [t1hard$1] (45) ; [t1fast$1] (46); [t1effort$1] (47);
MODEL C2: *!specifies the model at time 2 with constraints on thresholds*
%C2#1%
[t2learn$1] (11) ; [t2crdem$1] (12); [t2how$1] (13); [t2what$1] (14); [t2hard$1] (15) ; [t2fast$1] (16); [t2effort$1] (17);
%C2#2%
[t2learn$1] (21) ; [t2crdem$1] (22); [t2how$1] (23); [t2what$1] (24); [t2hard$1] (25) ; [t2fast$1] (26); [t2effort$1] (27);
%C2#3%
[t2learn$1] (31) ; [t2crdem$1] (32); [t2how$1] (33); [t2what$1] (34); [t2hard$1] (35) ; [t2fast$1] (36); [t2effort$1] (37);
%C2#4%
[t2learn$1] (41) ; [t2crdem$1] (42); [t2how$1] (43); [t2what$1] (44); [t2hard$1] (45) ; [t2fast$1] (46); [t2effort$1] (47);
MODEL C3: *!specifies the model at time 3 with constraints on thresholds*
%C3#1%
[t3learn$1] (11) ; [t3crdem$1] (12); [t3how$1] (13); [t3what$1] (14); [t3hard$1] (15) ; [t3fast$1] (16); [t3effort$1] (17);
%C3#2%
[t3learn$1] (21) ; [t3crdem$1] (22); [t3how$1] (23); [t3what$1] (24); [t3hard$1] (25) ; [t3fast$1] (26); [t3effort$1] (27);

```
%C3#3%
[ t3learn$1] (31) ; [ t3crdem$1] (32); [ t3how$1] (33); [ t3what$1] (34); [ t3hard$1] (35) ; [
t3fast$1] (36); [ t3effort$1] (37);
%C3#4%
[ t3learn$1] (41) ; [ t3crdem$1] (42); [ t3how$1] (43); [ t3what$1] (44); [ t3hard$1] (45) ; [
t3fast$1] (46); [ t3effort$1] (47);
OUTPUT:
svalues; !requests model starting values
tech15; !requests estimated transition probabilities for the class variables
```

6) Mplus input code for the three-step procedure to account for measurement error using classify-analyze strategy

For information about the three step procedure please see:

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: three-step approaches using Mplus. *Structural Equation Modeling: A Multidisciplinary Journal*, *0*(July), 1–13. doi:10.1080/10705511.2014.915181

Nylund-Gibson, K., Grimm, R., Quirk, M., & Furlong, M. (2014). A latent transition mixture model using the three-step specification. *Structural Equation Modeling: A Multidisciplinary Journal*, (February 2015), 1–16. doi:10.1080/10705511.2014.915375

STEP 1

First, we saved the starting values of the latent transition analysis model with measurement invariance across time points using Mplus input presented in point 4 in this supplementary material.

STEP 2

Second, we saved the classification into participants' most probable latent class. We fixed the measurement model of latent classes using the starting values from step 1. This has to be done separately for each categorical latent variable.

Mplus input file for the time 1 categorical latent variable:

DATA: FILE = data.dat;

VARIABLE:

[NAMES specified as before]

MISSING are all (-9); *!defines missing values coding*

USEVARIABLES ARE *!list of variables for the analysis at time 1*

t1learn t1crdem t1how t1what t1fast t1hard t1effort;

CATEGORICAL = all; *!specifies all used variables as categorical*

CLASSES = c1 (4); *!defines categorical latent variable c1 at time 1 with 4 latent classes*

AUXILIARY = *!defines variables that will not be used in the analyses*

! but will be included in the "savedata" command to enable further use

t2learn t2crdem t2how t2what t2fast t2hard t2effort

t3learn t3crdem t3how t3what t3fast t3hard t3effort

t1gender t1age t1exe t1tech t2exe t2tech t3exe t3tech

t2ssat t2sburn t3sburn t3ssat t4sburn t4ssat;

ANALYSIS:

TYPE = MIXTURE; *!defines mixture modelling*

STARTS 0; *!no initial random starting values are used since the measurement model is fixed at*

!the values obtained for the longitudinal model with measurement invariance

```
MODEL:
%OVERALL% !symbol @ replaces * to fix the estimate at a specific value
[ c1#2@1.00655 ];
[ c1#1@1.08878 ];
[ c1#3@0.24792 ];
%C1#2%
[ t1learn$1@0.50589 ] (1);
[ t1crdem$1@-0.10454 ] (2);
[ t1how$1@1.15822 ] (3);
[ t1what$1@4.59868 ] (4);
[ t1fast$1@2.41916 ] (5);
[ t1hard$1@5.11668 ] (6);
[ t1effort$1@2.62016 ] (7);
%C2#1%
[ t1learn$1@-0.12372 ] (8);
[ t1crdem$1@-1.12088 ] (9);
[ t1how$1@-3.19092 ] (10);
[ t1what$1@-0.37944 ] (11);
[ t1fast$1@2.79368 ] (12);
[ t1hard$1@4.79094 ] (13);
[ t1effort$1@2.57148 ] (14);
%C2#3%
[ t1learn$1@0.07057 ] (15);
[ t1crdem$1@-0.87732 ] (16);
[ t1how$1@1.46090 ] (17);
[ t1what$1@3.37868 ] (18);
[ t1fast$1@-0.89747 ] (19);
[ t1hard$1@-0.92056 ] (20);
[ t1effort$1@-0.42118 ] (21);
%C2#4%
[ t1learn$1@-0.92792 ] (22);
[ t1crdem$1@-1.98470 ] (23);
[ t1how$1@-15 ] (24);
[ t1what$1@-0.37149 ] (25);
[ t1fast$1@-0.44296 ] (26);
[ t1hard$1@-1.03830 ] (27);
[ t1effort$1@-0.23139 ] (28);
!the following command saves the most probable classification at time 1
SAVEDATA: file=c1.dat; save=cprob; missflag = 999;
```

Mplus input file for the time 2 categorical latent variable:

DATA: FILE = c1.dat;
VARIABLE: NAMES =
t1learn t1crdem t1how t1what t1fast t1hard t1effort
t2learn t2crdem t2how t2what t2fast t2hard t2effort
t3learn t3crdem t3how t3what t3fast t3hard t3effort
t1gender t1age t1exe t1tech t2exe t2tech t3exe t3tech
t2ssat t2sburn t3sburn t3ssat t4sburn t4ssat;
cprob1 cprob2 cprob3 cprob4 n1;
MISSING are all (999); *!defines missing values coding*
USEVARIABLES ARE *!list of variables for the analysis at time 2*
t2learn t2crdem t2how t2what t2fast t2hard t2effort;
CATEGORICAL = all; *!specifies all used variables as categorical*
CLASSES = c2 (4); *!defines categorical latent variable c2 at time 2 with 4 latent classes*
[AUXILIARY and ANALYSIS commands are specified in the same way as in time 1 input. MODEL command is also specified in the same way due to the longitudinal measurement invariance]
SAVEDATA: file=c2.dat; save=cprob; missflag = 999;

Mplus input file for the time 3 categorical latent variable:

DATA: FILE = c2.dat;
VARIABLE: NAMES =
t2learn t2crdem t2how t2what t2fast t2hard t2effort
t1learn t1crdem t1how t1what t1fast t1hard t1effort
t3learn t3crdem t3how t3what t3fast t3hard t3effort
t1gender t1age t1exe t1tech t2exe t2tech t3exe t3tech
t2ssat t2sburn t3sburn t3ssat t4sburn t4ssat;
n1 cprob1 cprob2 cprob3 cprob4 n2;
MISSING are all (999); *!defines missing values coding*
USEVARIABLES ARE *!list of variables for the analysis at time 3*
t3learn t3crdem t3how t3what t3fast t3hard t3effort;
CATEGORICAL = all; *!specifies all used variables as categorical*
CLASSES = c3 (4); *!defines categorical latent variable c3 at time 3 with 4 latent classes*
[AUXILIARY and ANALYSIS commands are specified in the same way as in time 1 input. MODEL command is also specified in the same way due to the longitudinal measurement invariance]
!the following command saves the most probable classification at time 1
SAVEDATA: file=c3.dat; save=cprob; missflag = 999;

STEP 3

Third, we fixed latent classes at the values established for the time-invariant measurement model while taking into account the measurement error. Please find a detailed description of the procedure in e.g., Nylund, Asparouhov, & Muthén, 2007.

```
DATA: FILE = c3.dat;
VARIABLE:   NAMES =
t3learn t3crdem t3how t3what t3fast t3hard t3effort
t1learn t1crdem t1how t1what t1fast t1hard t1effort
t2learn t2crdem t2how t2what t2fast t2hard t2effort
t1gender t1age t1exe t1tech t2exe t2tech t3exe t3tech
t2ssat t2sburn t3sburn t3ssat t4sburn t4ssat;
n1 n2 cprob1 cprob2 cprob3 cprob4 n3;
MISSING are all (999); !defines missing values coding
USEVARIABLES ARE !list of variables for the analysis at time 3
t3learn t3crdem t3how t3what t3fast t3hard t3effort;
usevar = n2 n3 n4; !modal classes assignment variables
nominal n2 n3 n4;
CLASSES = c1 (4) c2 (4) c3 (4);
ANALYSIS:
TYPE = MIXTURE;STARTS = 0;
MODEL:
%OVERALL%
c2 on c1; c3 on c2; !specifies an autoregressive structure
Model c1:
!Mixed model is specified to have just one indicator, a class assignment variable, and it is fixed
!at a value representing measurement error of the assignment. The values are obtained from the
!Step 2 output named “Logits for the Classification Probabilities for the Most Likely Latent
!Class Membership”
%C12#1%
[n1#1@4.427]; [n1#2@2.011]; [n1#3@-1.807];
%C1#2%
[n1#1@4.811]; [n1#2@6.417]; [n1#3@1.952];
%C1#3%
[n1#1@-1.035]; [n1#2@0.586]; [n1#3@2.043];
%C1#4%
[n1#1@-1.427]; [n1#2@-5.011]; [n1#3@-2.415];
Model c2:
%C2#1%
[n2#1@4.359]; [n2#2@1.803]; [n2#3@-2.071];
%C2#2%
```

```
[n2#1@4.799]; [n2#2@6.532]; [n2#3@2.200];
%C2#3%
[n2#1@-1.266]; [n2#2@0.354]; [n2#3@2.102];
%C2#4%
[n2#1@-1.431]; [n2#2@-5/296]; [n2#3@-2.840];
Model c3:
%C3#1%
[n3#1@4.713]; [n3#2@2.619]; [n3#3@-0.986];
%C3#2%
[n3#1@5.608]; [n3#2@7.536]; [n3#3@3.201];
%C3#3%
[n3#1@-0.593]; [n3#2@1.148]; [n3#3@2.789];
 %C3#4%
[n3#1@-1.287]; [n3#2@-4.024]; [n3#3@-1.729];
OUTPUT:
tech15; !requests estimated transition probabilities for the class variables
```

7) Mplus input code to estimate the autoregressive latent transition analysis model with stationary transition probabilities

To specify stationary transition probabilities, the code used for defining an autoregressive structure was replaced with the following code:

```
c1#1 ON c1#1 (t11);
c2#1 ON c1#2 (t12);
c2#1 ON c1#3 (t13);
c2#2 ON c1#1 (t21);
c2#2 ON c1#2 (t22);
c2#2 ON c1#3 (t23);
c2#3 ON c1#1 (t31);
c2#3 ON c1#2 (t32);
c2#3 ON c1#3 (t33);
c3#1 ON c2#1 (t11);
c3#1 ON c2#2 (t12);
c3#1 ON c2#3 (t13);
c3#2 ON c2#1 (t21);
c3#2 ON c2#2 (t22);
c3#2 ON c2#3 (t23);
c3#3 ON c2#1 (t31);
c3#3 ON c2#2 (t32);
c3#3 ON c2#3 (t33);
```

8) Mplus input code to estimate the autoregressive latent transition analysis model with covariates

To include the covariates in the model and to specify their time-invariant effects, the following code was added under MODEL OVERALL command:

```
c1 on t1age t1gender (d1-d6);
c1 on t1exe  t1tech (o1-o6);
c2 on t1age t1gender (d1-d6);
c2 on t2exe t2tech  (o1-o6);
c3 on t1age t1gender (d1-d6);
c3 on t3exe  t3tech (o1-o6);
```

9) **Mplus input code to estimate the autoregressive latent transition analysis model with distal outcomes**

To estimate means of the distal outcomes for each class, the following MODEL command was used (this is an example for job satisfaction, the same code was used for exhaustion):

```
Model c1:
%C1#1%
[n1#1@4.427]; [n1#2@2.011]; [n1#3@-1.807];
[t2ssat] (a1); t2ssat; !outcome means were labeled for each time point and each class
%C1#2%
[n1#1@4.811]; [n1#2@6.417]; [n1#3@1.952];
[t2ssat] (a2); t2ssat;
%C1#3%
[n1#1@-1.035]; [n1#2@0.586]; [n1#3@2.043];
[t2ssat] (a3); t2ssat;
%C1#4%
[n1#1@-1.427]; [n1#2@-5.011]; [n1#3@-2.415];
[t2ssat] (a4); t2ssat;
Model c2:
%C2#1%
[n2#1@4.359]; [n2#2@1.803]; [n2#3@-2.071];
[t3ssat] (b1); t3ssat;
%C2#2%
[n2#1@4.799]; [n2#2@6.532]; [n2#3@2.200];
[t3ssat] (b2); t3ssat;
%C2#3%
[n2#1@-1.266]; [n2#2@0.354]; [n2#3@2.102];
[t3ssat] (b3); t3ssat;
%C2#4%
[n2#1@-1.431]; [n2#2@-5/296]; [n2#3@-2.840];
[t3ssat] (b4); t3ssat;
Model c3:
%C3#1%
[n3#1@4.713]; [n3#2@2.619]; [n3#3@-0.986];
[t4ssat] (c1); t4ssat;
%C3#2%
[n3#1@5.608]; [n3#2@7.536]; [n3#3@3.201];
[t4ssat] (c1); t4ssat;
%C3#3%
[n3#1@-0.593]; [n3#2@1.148]; [n3#3@2.789];
```

```
[t4ssat] (c2); t4ssat;
%C3#4%
[n3#1@-1.287]; [n3#2@-4.024]; [n3#3@-1.729];
[t4ssat] (c3); t4ssat;

MODEL CONSTRAINT: !defines comparisons between classes
new (a12 a13 a14  a23 a24  a34  b12 b13 b14  b23 b24  b34
c12 c13 c14 c23 c24  c34  ab1 ab2 ab3 ab4
bc1 bc2 bc3 bc4 ac1 ac2 ac3 ac4);
!within-time comparisons
a12 = a1-a2; a13 = a1-a3; a14 = a1-a4; a23 = a2-a3;
a24 = a2-a4; a34 = a3-a4; b12 = b1-b2; b13 = b1-b3;
b14 = b1-b4; b23 = b2-b3; b24 = b2-b4; b34 = b3-b4;
c12 = c1-c2; c13 = c1-c3; c14 = c1-c4; c23 = c2-c3;
c24 = c2-c4; c34 = c3-c4;
!between time comparisons
ab1 = a1-b1; ab2 = a2-b2; ab3 = a3-b3; ab4 = a4-b4;
bc1 = b1-c1; bc2 = b2-c2; bc3 = b3-c3; bc4 = b4-c4;
ac1 = a1-c1; ac2 = a2-c2; ac3 = a3-c3; ac4 = a4-c4;
```