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Profiling a Spectrum of Mental Job Demands and their Linkages to Employee Outcomes

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Abstract: Working life is becoming more mentally demanding and intense due to technological acceleration. The present study explored employees' experiences of different mental job demands (MJDs) and their outcomes (job burnout, job performance, and meaning of work). We focused on intra- and inter-individual variations and possible harmful combinations of MJDs, which we explored via latent profile analysis (LPA). To identify harmful combinations of MJDs, we also investigated how the profiles of MJDs related to the outcomes of interest. The study was based on a diverse sample of Finnish employees ($n = 4,583$). LPA showed that both intra-individual and inter-individual variation characterized MJDs as we identified five latent profiles of MJDs. The most harmful profile, which predicted the most negative outcomes (particularly job burnout), was characterized by employees' scoring high on all MJDs. A profile characterized by low learning demands and moderate level of other MJDs was also a harmful combination in terms of outcomes. In contrast, a profile characterized by moderate level of learning demands and low level of other MJDs did not relate to negative outcomes. Altogether, the findings suggest that different MJDs may co-occur implying risks to employee well-being and performance. However, MJDs simultaneously form a complex spectrum that may differ within and between individuals.

Keywords: mental job demands, work intensification, job burnout, job performance, meaning of work, latent profile analysis

Contemporary working life is characterized by rapid technological acceleration in the form of increasing digitalization, robotization, and artificial intelligence, which are changing working conditions in many ways (see Chesley, 2014; Mustosmäki, 2017; Rosa, 2003; Paškvan et al., 2016). One hallmark of these changes is an intensification of work referring to work processes and work cultures, where the work effort required of employees has become more intense and efficacy-focused in terms of time and quality (e.g., Green, 2004; Kubicek et al., 2015; Mauno et al., 2019b; Mauno et al., 2020). In this study, we approach intensified working life from the perspective of mental job demands (henceforth MJDs), referring to a spectrum of recently

identified mental job demands which have intensified and increased due to technological and structural changes in working life and also to empowerment-focused management practices (see more, Chesley, 2014; Galy et al., 2012; Kubicek et al., 2015; Rosa, 2003; Mauno et al., 2019b; Mauno et al., 2020).

Specifically, we investigate whether Finnish blue- and white-collar workers ($N = 4,583$) experience MJDs in qualitatively different ways. To achieve this, we first examine how different MJDs combine by analyzing latent profiles (LPA) of MJDs, the method which enables us to model MJDs as multi-faceted and complex phenomena at the intra-individual and inter-individual levels (Laursen &

Hoff, 2006; Muthén, 2001; Spurk et al., 2020). LPA enables to identify homogeneous and heterogeneous groups (profiles) of individuals as regards the phenomena of interest (here MJDs), revealing also typical and atypical configurations/patterns of the constructs (see Bergman & Lundh, 2015; Spurk et al., 2020). Second, as MJDs typically entail stressors for employees with detrimental employee outcomes (Chesley, 2014; Fletcher et al., 2018; Franke, 2015; Kubicek et al., 2015), we also examine whether and how the profiles of MJDs relate to certain employee outcomes, that is, job burnout, job performance, and meaning of work. These outcomes were selected as they represent qualitatively different consequences and profile differences in them would also validate the profiles of MJDs (supporting criterion validity) (see Spurk et al., 2020). The main contribution of our study is two-fold. First, our research model includes various self-rated MJDs (described below), which have so far been studied only rarely due to the novelty of these demands. Second, if studied at all, MJDs have typically been analyzed as separate constructs without paying attention to their potential integrated properties or inter-relationships (at intra- and inter-individual level), which is focused here.

Theoretical underpinnings of MJDs

Overall, MJDs refer to the mental effort and thinking required at work to accomplish the (mental) tasks and to perform adequately at work (Galy et al., 2012; Zapf et al., 2014; Warm et al., 2008). However, no job demands occur in a vacuum but are typically inter-linked and additive (see e.g., Galy et al., 2012; Sweller, 1988). This may be particularly true regarding MJDs as such demands typically tax the same psychophysiological systems, e.g., short- and long-term memory, hence also causing cognitive load (e.g., Dillard et al., 2019; Sweller, 1988). Despite this systemic similarity, different cognitive load factors can be distinguished. Indeed, Galy et al. (2012) have distinguished three cognitive load factors, that is, task difficulty, time pressures, and arousal/alertness, each of these being embedded in cognitive load theory (CLT) (Sweller, 1988), which is also applicable in the context of work.

Specifically, CLT suggests that heavy mental workload requires the individual to allocate extra (mental) resources, which, in turn, impairs information processing efficiency and performance, and can also be distressing and mentally draining (e.g., Dillard et al., 2019; Sweller, 1988). Moreover, cognitive load factors can be divided into intrinsic and extrinsic (Sweller, 1988). Task difficulty belongs to the former, whereas time pressures and arousal belong to the latter category, although this distinction is not so strict in reality (Galy et al., 2012). Actually, these cognitive load factors stand in reciprocal relation to each other, and their effects are mostly additive, that is, the more cognitive load factors co-occur, the more distressed an individual is (Galy et al., 2012). In line with this assumption, empirical studies

have already shown that it is the interaction of these cognitive load factors which matters most. For example, Galy et al. (2012) showed that individuals' performance and mental efficiency were poorer when both task difficulty and time pressures were high and when their alertness was low. Furthermore, other studies have found that cognitive load not only impairs our performance but is also distressing (Dillard et al., 2019).

Inspired by these findings, it has been suggested that research should continue screening different cognitive load factors and their multiple outcomes (Galy et al., 2012). In the present study, cognitive load factors include five particular indicators of mental workload, which we introduce next.

Defining the MJDs of the present study

In the present study, the MJDs comprise five specific job demands, namely work intensification, intensified planning- and decision-making demands in relation to one's job or career, intensified skill- and knowledge-related learning demands at work, illegitimate tasks and interruptions at work. We will evaluate these MJDs through employees' cognitive appraisals/self-reports as employees' cognitive appraisal of their work environment is decisive when assessing how the work environment affects employees' well-being and performance (Lazarus & Folkman, 1984). All these MJDs are relatively new in work psychology and their self-report assessment has only recently been developed (see Fletcher et al., 2018; Kubicek et al., 2015; Semmer et al., 2015). Consequently, our study is one of the first attempts to investigate how a spectrum of perceived MJDs combines at two levels (intra- and inter-individual levels).

Intensified job demands (IJDs) refer to recently launched job stressors developed to characterize and assess the consequences of accelerated and intensified working life on employees' appraised mental workload (Korunka et al., 2015; Kubicek et al., 2015; Paškvan et al., 2016; Mauno et al., 2019b; Mauno et al., 2020). IJDs are an offshoot of social acceleration theory (Rosa, 2003), which claims that our activities in all life spheres, including working life, have accelerated, and the primarily fueling phenomenon underlying this is technological acceleration. Consequently, IJDs are currently highly relevant mental job stressors as technological acceleration in the form of digitalization, robotization, and artificial intelligence renders working life more intense and mentally demanding (Chesley, 2014; Mustosmäki, 2017). Specifically, IJDs manifest as three following inter-related job demands: (1) work intensification, (2) intensified planning- and decision-making demands in relation to one's work and career, and (3) intensified knowledge- and skill-related learning demands.

Work intensification describes the intensification of workload over time, including increased time-related demands throughout the working day, such as intensified pace of work, lack of breaks, and multitasking requirements at

work (see Green, 2004; Franke, 2015; Kubicek et al., 2015; Paškvan et al., 2016). We define work intensification as one form of MJDs as working hard, performing multitasking, and skipping breaks require a lot of mental effort from an employee. In the framework of CLT (Galy et al., 2012; Sweller, 1988), work intensification corresponds to time pressures as an indicator of cognitive load (at work).

Intensified job- and career-related planning and decision-making demands refer to the increased requirements for employees to autonomously plan and pursue their work goals and daily work tasks (i.e., job-related demands) and to take greater individual responsibility for their career management and employability (i.e., career-related demands). Indeed, employees may experience increased autonomy as a requirement to make individual decisions on setting and achieving work-related goals too frequently or as a need to perform their work too independently overall. Moreover, freedom to make self-directed choices concerning one's career development may impose excessive personal responsibility for employees to be able to maintain their attractiveness in the labor market (Korunka et al., 2015; Kubicek et al., 2015; Mauno et al., 2019b; Mauno et al., 2020). Such self-directness regarding working or career management might be stressful as it implies higher mental workload for employees.

The acceleration characterizing contemporary working life may also increase employees' experiences of mental workload in the form of intensified learning demands referring to a need to continuously update old information and acquire new work-relevant knowledge (Korunka et al., 2015; Kubicek et al., 2015; Paškvan et al., 2016; Mauno et al., 2019b; Mauno et al., 2020). Such pressures to adopt the latest professional knowledge exemplify the intensified knowledge-related learning demands. However, not only is there a need to constantly update one's work-relevant knowledge, but also one's skills, for example by learning new competencies that enable effective job performance in the face of intensified skill-related learning demands. Thus, learning demands are, by definition, mental demands to be included in the spectrum of MJDs. Viewed in the framework of CLT (Galy et al., 2012; Sweller, 1988), intensified job- and career-related planning and decision-making demands and learning demands illustrate intrinsic task difficulty (at work) but also share some features of time pressures due to intensification. There is some empirical evidence to show that these IJDs are also sources of stress at work associated with impaired well-being and health (e.g., Franke, 2015; Kubicek et al., 2015; Paškvan et al., 2016; Mauno et al., 2019b; Mauno et al., 2020).

In addition to these IJDs, workers may also experience other kinds of MJDs, to which we now turn. There may be tasks at work, which employees experience as inappropriate, irrelevant or unfair. Semmer et al. (2015) have called these tasks illegitimate tasks. Examples are when a nurse is required to write a report on a computer instead of caring for the patient, or when a teacher is struggling how to use new

software instead of teaching students. Illegitimate tasks threaten employees' work identity or core work roles and are thus self-threatening and often also include feelings of unfairness as expressed in the feeling that "I should not be doing this or nobody should be doing this", thereby, constituting a source of stress for employees (Eatough et al., 2016; Ma & Peng, 2019; Semmer et al., 2015). Actually, there are two types of illegitimate task, namely those which are unreasonable and those which are unnecessary. The former refers to tasks that an employee perceives to be incompatible with his/her work role and which should be done by someone else, whereas the latter refers to tasks which are simply a waste of time and resources and nobody should be doing those (Semmer et al., 2015).

We take the view that illegitimate tasks include cognitive load (Galy et al., 2012; Sweller, 1998) as they require complex cognitive appraisal and evaluation processes from an employee, thereby capturing the essence of intrinsic task difficulties (at work). Furthermore, they may also contain unwanted external stimulation, which is taxing an employee's alertness/vigilance and also constitutes one hallmark of cognitive load (distracting attention from core tasks). Finally, illegitimate tasks may also contain a time pressure component of cognitive load as often core tasks need to be performed alongside with extra-role tasks.

Illegitimate tasks have been found to relate to poorer well-being and job performance (see e.g., Eatough et al., 2016; Ma & Peng, 2019; Semmer et al., 2015), signifying that they are seriously taken job stressors. Moreover, it is possible that an ongoing "technological tsunami" at work may even increase illegitimate tasks as employees' attention will be increasingly needed in technological aspects of the work, which they may consider illegitimate, especially if core work tasks require other kinds of attention or behavior, e.g. human interaction, care, or creative thinking.

Interruptions at work have been defined in several ways, but this MJD typically refers to external or internal stimuli distracting a worker's mental resources from the primary work task towards disruptive stimuli, thereby also inhibiting progress in the primary task (Jett & George, 2003; Fletcher et al., 2018). Examples at the workplace are various, but include at least distracting noises, smells, images, conversations, information flow, or computer problems that may distract employees' attention from the core task at hand. The principles of effective work rely on employees' ability to engage freely in the mental actions needed at work and to allow employees to focus on primary tasks without interruptions or distractions (Liebl et al., 2012; Sander et al., 2019). Viewed in the light of CLT (Galy et al., 2012; Sweller, 1988), interruptions clearly contain cognitive load as they typically include attention-split/vigilance difficulties, which again deplete an employee's mental resources and efficiency (Hancock, 2017). Furthermore, interruptions may also involve time pressure, a core element of cognitive load, as work tasks need to be done in spite of interruptions. On this ground, interruptions are naturally

stressful, considering that they typically also inhibit progress in primary work tasks, which also may cause extra stress if the work goals are not achieved as expected (Sander et al., 2019; Seddigh et al., 2014).

There is empirical evidence indicating that perceived interruptions at work are stressors resulting in poorer well-being and job performance (Fletcher et al., 2018; Liebl et al., 2012; Lin et al., 2013; Sander et al., 2019; Seddigh et al., 2014). We assume that the acceleration occurring in working life right now may increase interruptions at work as it encourages open offices, multitasking ideology, and global connectivity (Green, 2004; Sander et al. 2019), all of which may increase interruptions at (core) tasks, culminating ultimately in higher mental load at work.

Aims and hypotheses

The *first aim* of this study is to examine how the five above-described MJDs combine intra- and inter-individual levels (via LPA) and reveal qualitatively different configurations at both levels (see Spurk et al., 2020). As MJDs form a spectrum of mental demands arising from cognitive load at work, we may expect at least some degree of interdependence. This assumption is also consistent with the CLT (Galy et al., 2012; Sweller, 1998), which argues that cognitive load factors (e.g., intrinsic and extrinsic cognitive properties of the tasks) may also co-occur or accumulate. Consequently, we hypothesize that we shall find a profile (group) of employees who score either high or low on all five MJDs defined above (H1). However, it is also possible to identify more diverse employee profiles in LPA; for example, those who score high on some dimensions of MJDs but low on others. LPA, like person-centered analysis methods more generally, are data-driven methods, implying that it is difficult to predict what kinds of profiles/clusters will emerge from the data, particularly if firm theoretical assumptions on profile characteristics are lacking. However, these more explorative data analysis methods allow us to better understand how different phenomena may combine within and between individuals (e.g., Muthén, 2001; Spurk et al., 2020). Actually, there are also theoretical reasons to expect individual variation in the profiles of MJD. Because stress appraisal is a crucial element in the stress process (see Brem et al., 2017; Lazarus & Folkman, 1984), there may be individual differences in the extent to which work characteristics (here MJD) are appraised as stressful or accumulating by an individual. Viewed in this light, LPA is one appropriate tool to explore typical and atypical configurations of job demands at intra- and inter-individual level (see also Spurk et al., 2020; Woo et al., 2018)

The *second aim* of this study is to investigate how the profiles of MJDs relate to three specific employee outcomes, i.e., job burnout, job performance, and meaning of work. These selected outcomes also form important criteria for the profiles of MJDs; the profiles should show meaningful variation in the outcomes or otherwise their criterion

validity might be insufficient (see Spurk et al., 2020). In this respect, we are particularly interested in identifying risk profiles of MJDs (co-occurrence of MJDs), which, in turn, should relate to negative employee outcomes (i.e., more burnout, poorer performance and meaning of work). Indeed, if MJDs are negative stressors at work, they should relate to negative employee outcomes, a proposition consistent with many job stress models (e.g., Karasek & Theorell, 1990; Siegrist, 1996; Warm et al., 2008; Zapf et al., 2014). As we expected to find a profile (group) of employees scoring high on all dimensions of MJDs (H1), we further hypothesize that belonging to this “high-risk group” would likely predict more job burnout, perceiving one’s job performance poorer and one’s work to be less meaningful (H2). Nevertheless, as already stated, it is equally possible to find more diverse configurations of MJDs as stress appraisal is also individualistic (Brem et al., 2017; Lazarus & Folkman, 1984). However, it is difficult to predict beforehand how these profiles would look like. Consequently, it makes no sense to pose hypotheses on their relations to employee outcomes.

Materials and methods

Participants and procedure

The present study is part of a larger research project (IJDFIN) examining MJDs and employee outcomes in Finland. Participants were sampled via trade unions as, of all Finnish employees, 73% belonged to some trade union in 2017 (Ministry of Employment and the Economy, 2018). Data were collected during spring-summer 2018 from the Trade Union of Education (OAJ), the Industrial Union (TL), Service Union United (PAM), and Trade Union Pro (Pro). The participants were chosen from among currently working members on the register of each labor union using random sampling with a total of 5,000 individuals per union. Participation in the survey study was voluntary; participants were adults and no physiological or health data was gathered.

The survey was filled out online and tested before data collection. A total of 4,583 respondents participated in the study ($n_{OAJ} = 2,434$, $n_{TL} = 647$, $n_{PAM} = 857$, $n_{Pro} = 645$). The mean response rate was 24% (OAJ members 48%, TL members 14%, PAM members 19%, Pro members 13%). More women (69%) participated in the study ($women_{OAJ} = 79\%$, $women_{TL} = 26\%$, $women_{PAM} = 75\%$, $women_{Pro} = 64\%$) than men, but compared to the trade unions’ respective memberships the distribution was significantly different only in TL and PRO. Over 50-year-olds were overrepresented for the OAJ and Pro in relation to membership (57% and 49% vs. 43% and 15% respectively), whereas under 20-year-olds and over 61-year-olds (2% and 4% vs. 9% and 15% respectively) were underrepresented for PAM and respondents under the age of 40 were underrepresented for TL (74% vs. 55%).

The sample in our analyses consisted of those 3,294 em-

ployees who had responded to five indicators of MJDs (i.e., work intensification, intensified job- and career-related planning- and decision-making demands, learning demands, illegitimate tasks, and interruptions at work). Of these respondents, 69% were women, their ages varied from 20 to 66 years ($M = 46.8$, $SD = 11.4$). A total of 51% were white-collar workers and 12% worked in managerial positions. Information about employees' level of education, working hours in week, and type of employment contract are described under control variables (see more in next section). These control variables – in addition to gender, age, occupational group, and managerial position – were included in the analyses if they had significant bivariate correlations with a dependent variable in regression analyses (see more in Results).

Measures

IJDs were measured using the Intensification of Job Demands Scale developed and validated by Kubicek and colleagues (2015). Respondents were asked to assess changes in mental job demands in their work organization during the last five years (or less, if a participant had been working less than five years). It is noteworthy that as *IJDs* try to capture a societal process of acceleration occurring in particular job demands in recent years (Rosa, 2003), a time-frame of this scale focuses on perceived changes in *IJDs* that have occurred in the past (Kubicek et al., 2015; Mauno et al., 2019b; Mauno et al., 2020). In this study, we used the following three subscales of *IJDs*: 1) *work intensification* (WI) including five items (e.g., "...ever more work has to be completed by fewer and fewer employees"), 2) intensified job-related and career-related planning and decision-making demands (IJCPDs) including five items concerning intensified *job-related* demands (e.g., "one increasingly has to check independently whether the work goals have been reached") and three items concerning intensified *career-related* demands (e.g., "one is increasingly required to maintain one's attractiveness for the job market, e.g., through advanced education, networking"), 3) intensified *learning demands* (ILDs) including six items (e.g., "one has to update one's knowledge level more frequently" and "one increasingly has to familiarize oneself with new work processes"). The response scale was a five-point Likert-scale (1 = not at all, 5 = completely), higher scores reflecting more frequent/higher intensified job demands (WI: $M = 3.66$, $SD = 1.07$; IJCPDs: $M = 3.39$, $SD = .87$; ILDs: $M = 3.74$, $SD = 1.00$). Cronbach's alpha coefficients for WI, IJCPDs, and ILDs were .89, .88, and .95 respectively.

Illegitimate tasks were assessed using eight items from the Bern Illegitimate Tasks Scale (Semmer et al., 2010). The scale includes four items describing unnecessary tasks (e.g., "Do you have work tasks to take care of which keep you wondering if they have to be done at all?") and four items characterizing unreasonable tasks (e.g., "Do you have work tasks to take care of which you believe should be

done by someone else?"). Answers were given on a five-point Likert scale (1 = never, 5 = always), higher scores reflecting more illegitimate tasks ($M = 2.95$, $SD = .80$). Cronbach's alpha coefficient was .90.

Interruptions at work was evaluated via distractions, which were assessed using five items measuring *distractions* from the Interruption Scale developed by Fletcher and colleagues (2018; e.g., "It was hard to keep my attention on my work because of distractions in my workplace", "A noise or other distraction interrupted my workflow".) The sub-scale of distractions was selected to describe interruptions at work as it indicated the most consistent relationships with the employee outcomes in a validation study (Fletcher et al., 2018). Answers were given on a six-point Likert scale (1 = never, 6 = very frequently), higher scores reflecting more distractions ($M = 3.34$, $SD = 1.11$). Cronbach's alpha coefficient was .88.

Job burnout refers to a health impairment in response to chronic stressors at work including the dimensions of exhaustion, cynicism, and (lower) professional efficacy (Maslach Schaufeli, & Leiter, 2001). In the present study, burnout was evaluated via *job exhaustion* and *cynicism*, both of which were assessed with three items from the Bergen Burnout Indicator-9, the reliability and validity of which have been shown to be high in Finland (Feldt et al., 2014; Salmela-Aro et al., 2011). The items were rated on a six-point Likert scale (1 = completely disagree, 6 = completely agree), higher scores reflecting greater job exhaustion ($M = 3.29$, $SD = 1.19$) and more cynicism ($M = 2.78$, $SD = 1.28$). Cronbach's alpha coefficient for the exhaustion scale was .75 and for the cynicism scale .87.

Job performance refers to employees' behaviors and actions related to the goals of their work organization (Campbell, 1990). Job performance was operationalized via *task performance*, which was assessed with four items from the Individual Work Performance Questionnaire (e.g., "I was able to plan my work so that I finished it on time"; Koopmans et al., 2016). The items were rated on a five-point Likert scale (1 = rarely, 5 = always), higher scores reflecting better performance ($M = 3.58$, $SD = .73$). Cronbach's alpha coefficient for the task performance scale was .79.

Meaning of work refers to an individual interpretation of what work or the role of work signifies in the life context influenced by the social context (Rosso et al., 2010). In this study, *meaning of work* was assessed with four items from a positive meaning of work-scale based on the Work and Meaning Inventory Questionnaire (e.g., "I have found a meaningful career"; Steger et al., 2012). The items were rated on a seven-point Likert scale (1 = completely disagree, 7 = completely agree), higher scores reflecting more positive meaning of work ($M = 5.29$, $SD = 1.27$) Cronbach's alpha coefficient was .90.

Table 1*Intercorrelations between the Study Variables*

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. WI	–														
2. IJCPDs	.54***	–													
3. ILDs	.41***	.46***	–												
4. Illeg. tasks	.56***	.39***	.28***	–											
5. Distractions	.43***	.29***	.30***	.45***	–										
6. Exhaustion	.58***	.32***	.29***	.46***	.42***	–									
7. Cynicism	.31***	.16***	.02	.40***	.33***	.50***	–								
8. Performance	-.28***	-.08***	-.07***	-.30***	-.31***	-.39***	-.37***	–							
9. Work meaning	-.05**	.03	.23***	-.17***	-.10***	-.16***	-.63***	.29***	–						
10. Gender	-.15***	-.06***	-.20***	-.02	-.18***	-.18***	.01	-.01	-.16***	–					
11. White-collars	.16***	.09***	.36***	.11***	.15***	.17***	-.17***	-.01	.48***	-.25***	–				
12. Contract type	.06**	.01	.08***	.07***	.05**	.03	.10***	-.03	-.09***	.05**	-.17***	–			
13. Manager	.02	.07***	.05**	.03	-.02	.04*	-.04*	.00	.09***	.05**	.03*	.09***	–		
14. Education	.15***	.16***	.35***	.13***	.18***	.16***	-.07***	-.01	.30***	-.19***	.62***	-.09***	.06***	–	
15. Working hours	.19***	.16***	.09***	.14***	.07***	.21***	.03	-.08***	.02	.14***	.05**	.11***	.18***	.02	–
16. Age	.03*	.02	.21***	.03	.09***	-.01	-.03	.02	.16***	-.01	.21***	.26***	.06**	.08**	.04*

Note. WI = work intensification; IJCPDs = intensified job-related and career-related planning and decision-making demands; ILDs = intensified learning demands; illeg. tasks = illegitimate tasks; gender: 0 = women, 1 = men; white-collars: 0 = no, 1 = yes; contract type: 0 = temporary employment contract, 1 = permanent employment contract; manager = managerial position: 0 = no, 1 = yes; education: 1 = further vocational qualification or matriculation examination certificate, 2 = specialist vocational qualification, 3 = higher vocational level qualification, 4 = polytechnic qualification or bachelor degree, 5 = university degree, 6 = university postgraduate degree; working hours = working hours in week.

* $p < .05$, ** $p < .01$, *** $p < .001$, two-tailed.

Control variables of gender (0 = female, 1 = male), occupational group, type of employment contract, managerial position, education, hours worked per week, and age were included in the regression analyses when there was a significant correlation between the control variable and the dependent variable (see Table 1). Occupational group was coded as 0 = not white-collar worker (49%), 1 = white-collar worker (51%). The type of employment contract was coded as 0 = temporary (87%), 1 = permanent (13%). Managerial position was coded as 0 = no (88%), 1 = yes (12%). Education was coded as follows: 1 = vocational qualification or matriculation examination certificate (5%), 2 = specialist vocational qualification (25%), 3 = higher vocational level qualification (6%), 4 = polytechnic qualification or bachelor's degree (19%), 5 = university degree (42%), 6 = university postgraduate degree; licentiate or doctoral degree (3%). The average hours worked per week were 37.7 ($SD = 7.7$). The mean age was 46.8 years ($SD = 11.4$).

Data analysis

The main analytical tools in this study were latent profile analysis (LPA) and structural equation modeling (SEM). Specifically, LPA is a person-centered method of analysis enabling the identification of homogeneous and heterogeneous groups (profiles, patterns) of individuals as regards the phenomenon of interest (here MJDs) by utilizing mean value information at both intra-individual and inter-individual levels (see Muthén, 2001; Spurk et al., 2020; Woo et al., 2008). We perceive that one benefit of LPA is actually practice-oriented; LPA allows to find also smaller and unpredicted (atheoretical/atypical) groups of individuals in relation to the analyzed phenomena, which again might have important implications for those individuals, e.g., higher risks for health problems.

Here, LPA was implemented using Mplus statistical package (version 8; Muthén & Muthén, 1998–2017) to identify the number of latent profiles of respondents based on their individual responses to the five indicators of MJDs: WI, IJCPDs, ILDs, illegitimate tasks, and distractions. In LPA, participants sharing the same profile have similar mean estimates in the selected MJDs (Muthén, 2001; Tein et al., 2013). We applied models with the local independence and homogeneity of variance and used maximum likelihood robust estimation in order to take into account the skewness of analyzed variables. The LPA included the participants who had full data for all five MJDs ($n = 3,294$). The choice of the number of profiles followed the established procedure (Celeux, & Soromenho, 1996; Nylund et al., 2007; Tein et al., 2013). In the absence of general consensus of the best criteria for determining the number of profiles (Nylund et al., 2007), we based our decision on several statistical tests and reasonable content in profiles including adequate disparity of profiles, as the number of profiles may be overestimated in LPA (Bauer & Curran, 2003). We used likelihood ratio statistical tests (Lo-Mendell-Rubin tests; $p < 0.05$; Celeux & Soromenho, 1996), information criterion tests (Bayesian Information

Criterion, BIC, and Akaike's Information Criterion, AIC), the estimates of which are smaller when the model fits better data comparison with the alternative model, and entropy-based criterion (scale 0–1, good entropy > 0.80 Celeux and Soromenho 1996). One benefit of LPA over more traditional person-centered analysis methods (e.g., cluster analysis) is that LPA provides these statistical rigorous tests to compare the number of profiles in the data.

We used two variables, both of which reflect latent profiles of MJDs. In LPA executed by Mplus, each participant gets a *posterior probability* (henceforth PP) to belong to each one of the latent profiles, thus the number of PP variables is equal to that of the latent profiles (Muthén & Muthén, 1998–2017). For example, from the analysis including five latent profiles, every participant gets five PPs which represent participant's probability (0–100) to belong to each profile and each of these probabilities can be used as a separate PP variable. Thus, PPs offer more information about each participant than one simple categorical clustering variable which was the main reason why we used PPs as separate continuous variables in SEM modeling as explanatory variables. The second variable which reflected latent profiles of MJDs in our analyses was a categorical clustering variable which represented a respondent's *most likely latent profile membership* (henceforth MLP). A participant's MLP was determined by comparing his/her PPs to belong in each profile and choosing the profile which had the highest probability. The scale of MLP was 1–5 as the LPA solution included five latent profiles (see Results). MLP was used for naming profiles and descriptive analyses. Each latent profile was interpreted and named after its most prominent content comparing the standardized sample means of five MJDs for the profile.

The associations between MJDs and control variables were studied using Chi-square tests for dichotomous variables (gender, occupational group, type of employment contract, managerial position) and equality tests of means across profiles among variables modeled as continuous variables (education, hours worked per week, and age) using the modified BCH method in Mplus (Asparouhov & Muthén, 2018). Before SEM analyses we also examined the correlations of the variables studied including control variables (see Table 1). Descriptive and correlation analyses were conducted using IBM SPSS Statistics (Version 25).

Next, SEM was performed to analyze the relationships between the (MJDs) profiles and dependent variables (three employee outcomes as latent constructs). We used the SEM latent variable framework as it takes into account measurement errors which are associated with observed variables (Kline, 2011). These SEM analyses would also validate our profile solution: the (MJDs) profiles should show meaningful and significant associations with the employee outcomes studied, otherwise their criterion validity would be insufficient (see also Spurk et al., 2020). In SEM, we used separate PP variables (see the description above), each representing one MJDs' profile, as explanatory variables. We used PPs as they yielded more information about each

participant compared to one categorical MLP variable.

When PP variables were included in SEM, one of them was dropped out due to statistical limitations, as including all PPs in the same SEM caused unidentifiable model. The reason for this is that high correlation among the explanatory variables violates the assumption for linear regression (the absence of multicollinearity) and leads to numerical problems (Tabachnick & Fidell, 2013). This was the case here, as PPs were dependent on each other and the sum of the probabilities from all PPs was 100 for each participant. However, this dependency between PPs also signified that the information of the dropped profile was still affecting statistics in the SEM, even though PP in question was removed from the analysis. As the LPA solution included five latent profiles (see Results), four PPs representing MJDs' profiles were entered simultaneously into the SEM model as explanatory variables. We dropped a latent profile, which was mostly characterized by low MJDs, as we hypothesized that higher MJDs would be particularly stressful for employees (e.g., Galy et al., 2012; Karasek & Theorell, 1990; Zapf et al., 2014). Thus, latent profiles characterized by higher MJDs were more relevant for our purposes.

Specifically, four SEM models were executed, e.g., one model for each dependent variable (job exhaustion, cynicism, task performance, meaning of work) using maximum likelihood robust estimation in Mplus. We further compared the magnitude of the significant effects of the MJDs' profiles (four PP variables) on dependent variables with each other in the same SEM using the absolute values of the confidence intervals of the standardized regression coefficients (b^*). The effects of MJDs' profiles were interpreted as statistically significantly different if the confidence intervals of 95% did not overlap. Control variables were included in the SEM models if they had a significant bivariate correlation with a dependent variable ($p < .05$; see Table 1).

For SEM models, we applied the missing data approach using Mplus statistical package (Version 8) which handles missing values through full information maximum likelihood procedure (FIML; see Muthén & Muthén, 1998–2017). The missing data percentages in the dependent variables varied from 2.3% (task performance) to 5.1% (work meaning). The corresponding proportions for control variables were 0.2% in gender, 0% in occupational group, 10.5% in type of employment contract, 9.7% in managerial position, 0% in education, 11.4% in hours worked per week, and 0.1% in age. The model fit for SEM models was evaluated using Chi-square values (χ^2), comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The cutoff values were .95 for CFI and TLI, .06 for RMSEA, and .08 for SRMR (Hu & Bentler, 1999).

Results

Identifying the profiles of MJDs: LPA analysis

Several LPA models were executed each with a different number of latent profiles following the established procedure (Celeux & Soromenho, 1996; Nylund et al., 2007; Tein et al., 2013). According to the Lo-Mendell-Rubin tests, the model including five latent profiles fitted better than the model with four profiles (VLMR and LMR, $p < .001$; Table 2) and the model with six profiles was not a better solution than the five profiles model (VLMR and LMR, $p = .776$; Celeux & Soromenho, 1996; Tein et al., 2013), which supported to the choice of five profiles. The entropy-based criterion for five latent profiles was also slightly better (.94) than for six profiles (.93). Importantly, from the viewpoint of our research aim, the solution with five latent profiles also had a meaningful content sorting out profiles including higher MJDs from the profile of lower MJDs. These findings supported the choice of five profiles, which was selected for further analyses. It is also noteworthy that even though the test values of log-likelihood, BIC, and AIC were slightly better for the model of six profiles than that of five profiles, the six profile solution did not indicate any new meaningful profiles as regards the content. Actually, the sixth profile was identical in content to the solution of five profiles, the only difference being slightly higher levels of means for each MJD.

We named the latent profiles after their most prominent content based on the standardized sample means of five MJDs for each profile as follows (see Figure 1): *Low mental demands* (LMD), *Moderate learning demands and low other mental demands* (MLD), *Low learning demands and moderate other mental demands* (LLD), *Moderately high IJDs and moderate illegitimate tasks and distractions* (MHIJD), and *High mental demands* (HMD). The most likely latent profile membership for respondents was MHIJD (29.7%) and the most unlikely membership was LMD (14.0%) according to the estimated posterior probabilities. The corresponding shares were 21.2% for MLD, 18.8% for LLD, and 16.4% for HMD.

Comparing the latent profiles with each other, LMD and HMD were easily distinguished due to their distinct quantitative differences for every MJD (see Figure 1). Fewest MJDs accumulated in the profile of LMD and the greatest number of MJDs for HMD. MHIJD was characterized the second highest MJD except for illegitimate tasks, which were at the second highest level in the profile of LLD. Among MLD, LLD, and MHIJD we identified different combinations in experiencing MJDs. Specifically, LLD was characterized by low learning demands (about 1 SD below mean) when MLD and MHIJD were close to their means. Thus, employees having in their MJD profile LLD or LMD did not report high learning demands in their jobs. MHIJD was characterized by moderately high IJDs (about 0.5 SD above the mean), slightly more distractions than average

and average level of illegitimate tasks. MLD was characterized by low WI, illegitimate tasks, and distractions (all at least 0.5 SD below mean), slightly fewer IJCPDs than av-

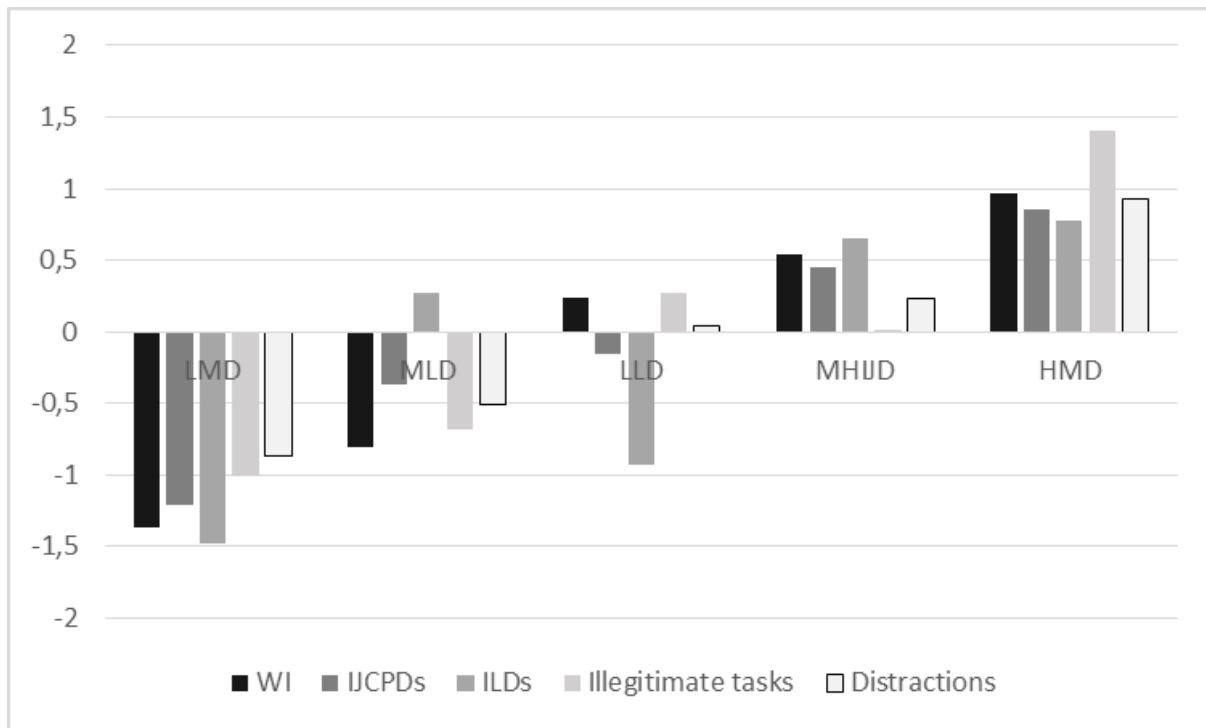
erage, and slightly higher learning demands than average. In sum, the LPA results revealed different combinations of experiencing MJDs.

Table 2
The Latent Profiles Based on Their Most Likely Latent Class Membership

Number of profiles	VLMR	LMR	LogL	BIC	AIC	Entropy	n (%)
1	-	-	-190311	381221	380769	-	3294 (100)
2	.000	.000	-175104	351115	350432	.95	1414 (42.9), 1880 (57.1)
3	.003	.003	-170259	341732	340817	.94	675 (20.5), 1183 (35.9), 1436 (43.6)
4	.001	.001	-166361	334245	333099	.94	526 (16.0), 645 (19.6), 961 (29.2), 1162 (35.3)
5 ¹⁾	.000	.000	-163964	329758	328379	.94	464 (14.1), 539 (16.4), 617 (18.7), 693 (21.0), 981 (29.8)
6	.776	.776	-162527	327193	325582	.93	359 (10.9), 434 (13.2), 488 (14.8), 527 (16.0), 690 (20.9), 796 (24.2)

Note. VLMR = Vuong-Lo-Mendell-Rubin likelihood ratio test, LMR = Lo-Mendell-Rubin adjusted lrt test, LogL= Log-likelihood, BIC = Bayesian information criterion, AIC = Akaike’s information criterion. ¹⁾The selected profile solution for further analyses.

Figure 1.
Standardized Sample Means of the Job Mental Demands for the Latent Profile Variables Based on Respondents’ Most Likely Latent Class Member.



Note. LMD = Low mental demands, MLD = Moderate learning demands and low other mental demands, LLD = Low learning demands and moderate other mental demands, MHJD = Moderately high IJDs and moderate illegitimate tasks and distractions, HMD = High mental demands; WI = work intensification; IJCPDs = intensified job-related and career-related planning and decision-making demands; ILDs = intensified learning demands.

Analyzing the relationships between the profiles of MJDs and background factors

To further validate the profile solution reported above, we compared profiles with regard to certain background factors, which also served as control variables in subsequent analyses. The likelihood of belonging to MJD profiles was different for women and men (Chi-square 110.798, $df = 4, p < .001$). Men had more frequently profiles in LMD and LLD than women, whereas women had more frequently profiles in MHIJD and HMD than men according to the adjusted residuals (all $p < 0.05$). However, there was no gender difference in the profile of MLD. When the occupational group (non-white-collar worker vs. white-collar worker) was included in the analysis using a three-way contingency table, men had MLD profile more frequently than women ($p < .05$) among the white-collar workers. Moreover, when the occupational group was taken into account, there was no gender difference in the profiles of LLD and HMD. Thus, occupational group was a more important factor than gender for the MJDs' profiles. When

profiles were compared with regard to union membership only, the likelihood of belonging to MJD profiles was different for white-collar workers than others (Chi-square 338.642, $df = 4, p < .001$). White-collar workers had more frequently profiles in MLD (58%), MHIJD (62%), and HMD (68%) compared to other workers, whereas other workers had more frequently profiles in LMD (76%) and LLD (68%).

Type of employment contract and managerial position revealed few differences among the employees as regards their most likely MJDs profile. Temporary employment contract was more frequent among those most likely to belong to the LMD profile group, whereas temporary contract was less frequent among those whose profile was HMD (Chi-square 24.750, $df = 4, p < .001$). Thus, permanent job contract seems to be associated with higher MJDs. Managerial position was rarer among employees with LMD profile and more frequent among those with MHIJD profile (Chi-square 20.928, $df = 4, p < .001$).

Table 3
Equality Tests of Means across Profiles in Background Variables

	Education		Working hours per week		Age	
	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>
LMD	2.89	.07	36.33	.39	43.26	.57
MLD	3.97	.05	36.14	.32	48.48	.45
LLD	3.29	.06	37.56	.33	44.64	.49
MHIJD	4.20	.04	38.75	.27	47.92	.36
HMD	4.22	.05	39.30	.40	47.96	.49
	χ^2		χ^2		χ^2	
LMD vs. MLD	157.50***		.14		50.99***	
LMD vs. LLD	19.19***		5.82*		3.32	
LMD vs. MHIJD	277.90***		26.54***		47.62***	
LMD vs. HMD	240.55***		28.61***		39.41***	
MLD vs. LLD	70.82***		9.40**		32.75***	
MLD vs. MHIJD	10.35**		37.78***		.90	
MLD vs. HMD	10.35**		38.38***		.62	
LLD vs. MHIJD	151.93***		7.63**		28.43***	
LLD vs. HMD	132.98***		11.23**		23.20***	
MHIJD vs. HMD	.10		1.24		.00	

Note. LMD = low mental demands, MLD = moderate learning demands and low other mental demands, LLD = low learning demands and moderate other mental demands, MHIJD = moderately high intensified job demands and moderate illegitimate tasks and distractions, HMD = high mental demands, χ^2 = Chi-square. * $p < .05$, ** $p < .01$, *** $p < .001$, two-tailed.

Table 4
Associations between Profiles of Mental Job Demands and Outcomes

Predictor	Job exhaustion		Cynicism		Task performance		Meaning of Work	
	<i>b</i> *	<i>SE</i>	<i>b</i> *	<i>SE</i>	<i>b</i> *	<i>SE</i>	<i>b</i> *	<i>SE</i>
MLD	.13***	.02	.01	.02	-.01	.03	.08***	.03
LLD	.43***	.02	.29***	.02	-.17***	.03	-.12***	.03
MHIJD	.52***	.02	.22***	.03	-.13***	.03	.01	.03
HMD	.69***	.02	.45***	.03	-.22***	.03	-.13***	.03
Gender	-.13***	.02					-.03	.02
White-collars	.07**	.02	-.24***	.02			.44***	.02
Contract type	-.01	.02	.04*	.02	-.03	.03	-.04*	.02
Manager	.01	.02	-.06**	.02			.07***	.02
Education	-.00	.02	.03	.02			.00	.02
Working hours	.17***	.02			-.05	.03		
Age							.09***	.02
<i>R</i> ²	.486		.223		.053		.297	

Note. MLD = moderate learning demands & low other mental demands, LLD = low learning demands and moderate other mental demands, MHIJD = moderately high intensified job demands and moderate illegitimate tasks and distractions, HMD = high mental demands; gender: 0 = women, 1 = men; white-collars: 0 = no, 1 = yes; contract type: 0 = temporary employment contract, 1 = permanent employment contract; manager = managerial position; 0 = no, 1 = yes; education: 1 = further vocational qualification or matriculation examination certificate, 2 = specialist vocational qualification, 3 = higher vocational level qualification, 4 = polytechnic qualification or bachelor degree, 5 = university degree, 6 = university postgraduate degree; working hours = working hours in week; *b** = standardized regression coefficient, *SE* = standard error, *R*² = multiple correlation squared. * *p* < .05, ** *p* < .01, *** *p* < .001, two-tailed.

Furthermore, equality tests of means across profiles showed that the latent profiles differed significantly from each other in most of the pair comparisons with regard to level of education, hours worked per week, and age (Table 3). Level of education was highest among those employees whose most likely profile was HMD and MHIJD. The next highest level of education was that among those whose most likely profile was MLD, which may be because MLD was also characterized by third greatest learning demands on average after HMD and MHIJD (see Figure 1). Level of education was lowest among those employees whose most likely profiles were LMD and LLD. In sum, the higher MJDs (HMD and MHIJD) were associated with higher level of education and vice versa, the lower MJDs (LMD) were associated with lower level of education. Hours worked per week were highest among those employees whose most likely profiles were HMD and MHIJD and lowest among employees whose most likely profiles were LMD and LLD. Profiles of MLD, HMD, and MHIJD were more typical for older employees, and LMD and LLD for younger employees.

Relationships between Latent Profiles and Employee Outcomes: SEM analyses

We ran four SEM models in order to explore whether the profiles of MJDs were associated with the selected outcomes (exhaustion, cynicism, task performance, and mean-

ing of work). The results showed that MLD, LLD, MHIJD, and HMD profiles were significantly associated with a greater job exhaustion (*b** = .13, *b** = .43, *b** = .52, *b** = .69 respectively, all *p* < .001; see Table 4). The effect of HMD was significantly stronger compared to MLD (*CI* 95%: .09, .17), LLD (*CI* 95%: .39, .48), and MHIJD (*CI* 95%: .47, .57) as the confidence intervals for HMD (*CI* 95%: .64, .73) did not overlap with the confidence intervals for the other profiles. The difference between the effects of LLD and MHIJD was not statistically significant but compared to other profiles MLD was significantly less associated with job exhaustion.

Latent profiles of LLD, MHIJD, and HMD were significantly associated with a greater cynicism (*b** = .30, *b** = .22, *b** = .45 respectively, all *p* < .001) but MLD was not. HMD (*CI* 95%: .40, .50) was significantly more associated with cynicism than LLD (*CI* 95%: .24, .34) and MHIJD (*CI* 95%: .17, .27) but the difference between the effects of LLD and MHIJD was not statistically significant as the confidence intervals of the coefficients overlapped.

Latent profiles of LLD, MHIJD, and HMD were significantly associated with poorer task performance (*b** = -.17, *b** = -.13, *b** = -.22 respectively, all *p* < .001) but MLD was not. Although the coefficient of HMD (*CI* 95%: -.16, -.27) was greatest, it was not significantly greater than the coefficients of LLD or MHIJD (*CI* 95%: -.12, -.23, *CI* 95%: -.07, -.18 respectively). Also, the difference between the effects of LLD and MHIJD was not statistically significant

as their confidence intervals overlapped.

Latent profiles of MLD, LLD, and HMD were also significantly associated with meaning of work ($b^* = .08$, $b^* = -.12$, $b^* = -.13$ respectively, all $p < .001$) but MHIJD was not. Thus, the latent profiles of LLD or HMD were associated with less positive meaning of work and MLD was associated with more positive meaning of work. The differences between HMD (CI 95%: $-.09$, $-.18$), LLD (CI 95%: $-.07$, $-.17$) and MLD (CI 95%: $.04$, $.13$) were not statistically significant when comparing to the absolute values of confidence intervals which overlapped. Although MHIJD was characterized by second highest MJDs (excluding learning demands), it had no significant association with meaning of work.

The fits for the SEM models were all excellent or acceptable: job exhaustion $\chi^2(20) = 208.530$, $p < .001$; CFI = .948; TLI = .915; RMSEA = .053; SRMR = .015; cynicism $\chi^2(16) = 89.013$, $p < .001$; CFI = .985; TLI = .975; RMSEA = .037; SRMR = .010; task performance $\chi^2(20) = 247.539$, $p < .001$; CFI = .971; TLI = .956; RMSEA = .059; SRMR = .020; meaning of work $\chi^2(32) = 217.582$, $p < .001$; CFI = .977; TLI = .967; RMSEA = .042; SRMR = .012.

In sum, of the latent profiles, HMD (high mental demands) was most strongly associated with job exhaustion and cynicism compared to other latent profiles. The most adverse and straightforward linearity was detected between MJDs and job exhaustion. Our results would also suggest that high mental demands may undermine task performance but the coefficient of determination explanation for the model was much lower ($R^2 = .053$) than what we found for job exhaustion, cynicism, and meaning of work ($R^2 = .486$, $R^2 = .223$, $R^2 = .297$).

Discussion

Working life has become more mentally demanding in the past decade and this trend is likely to continue due to technological acceleration in the form of digitalization, robotization, and artificial intelligence (e.g., Chesley, 2014; Korunka et al., 2015; Kubicek et al., 2015; Paškvan et al., 2016; Mauno et al., 2019b; Mauno et al., 2020). We focused here on a spectrum of *mental job demands (MJDs)* by exploring how qualitatively different MJDs (i.e., intensified job demands, illegitimate tasks, and interruptions at work) combine within- and between-persons.

The results showed that MJDs do co-occur, forming risk profile(s) with harmful employee outcomes, i.e., more job burnout, poorer job performance and meaning of work. This finding is consistent with the cognitive load theory, which suggests that cognitive load factors, also at work, do co-emerge and this, in turn, has negative additive effects on well-being and performance (e.g., Galy et al., 2012; Sweller, 1998). However, the results also showed that the MJDs studied are qualitatively different and do not always co-occur or accumulate, which suggests diversity in profiles across individuals. This finding, in turn, is consistent

with the transactional stress model (Lazarus & Folkman, 1984), which suggests that stress appraisal is individualistic, implying that there are individual differences concerning which environmental factors are perceived as stressful and accumulating, and to what extent (see also Brem et al., 2017). According to our best knowledge, this is the first single study to investigate the profiles of contemporarily relevant MJDs and their employee outcomes by combining person-centered (identifying typical and atypical MJDs' profiles) and variable-centered (analyzing the outcomes of MJDs' profiles) approaches.

Co-occurrence of MJDs

Our first hypothesis, which suggested that we would find profiles characterized by either a high or low level of MJDs, was supported. Indeed, MJDs co-occur within the person-level, but only to some extent, as 30% the participants had either high (HMD profile) or low profile for MJDs (LMD profile). The former group scored high and the latter low on all five MJDs. On the MJDs studied, employees scored particularly high (or conversely low) on illegitimate tasks (unnecessary and unreasonable tasks), which can therefore be regarded as one typical hallmark of today's MJDs (see Eatough et al., 2016; Ma & Peng, 2019; Semmer et al., 2015). However, our analytical approach also allowed us to identify more diversity in the profiles (see also Spurk et al., 2020). For instance, we found a large profile (30%) where employees scored relatively high on intensified job demands (IJDs; work intensification, intensified planning- and decision-making demands, and learning demands (see Kubicek et al., 2015, Mauno et al., 2019b; Mauno et al., 2020), but moderately on illegitimate tasks and interruptions at work (MHIJD profile). On the one hand, the dimensions of IJDs tend to correlate, but on the other hand, they are also distinguishable constructs with different antecedents and outcomes as indicated in earlier studies (Korunka et al., 2015; Kubicek et al., 2015; Mauno et al., 2019b; Mauno et al., 2020).

Another interesting less common profile (19%) was characterized particularly by low learning demands at work (LLD profile). This profile is not totally new, as Karasek and Theorell (1990) have already shown that some jobs are characterized by lower learning opportunities (describing passive work). However, we consider this profile surprising as blue-collar jobs are nowadays also assumed to be more mentally demanding, including requirements for lifelong learning. Apparently, this is not yet the case but may be more so in future with technological acceleration in industry and services. Moreover, it should also be recalled that our data also included less educated (blue-collar) workers, who were over-represented in the profiles of low learning demands and moderate other mental demands (LLD) and low overall MJDs (LMD). However, it is also noteworthy that only 14% of the employees belonged to the profile with low MJDs, signifying that today's working life seems

to be mentally demanding for a vast majority of employees (see Galy et al., 2012; Kubicek et al., 2015).

Noteworthy is that we also executed cluster analysis, as a post-hoc analysis, using two-step clustering method (via SPSS). We explored the correspondence between clusters and profiles found in LPA. Specifically, we tested models with 2-7 clusters which all showed adequate cluster quality (detailed results available from authors upon request). Only models for 2, 5, and 7 clusters were acceptable according to recommended statistics. However, we do not know if there were any significant differences between these cluster solutions as they all indicated adequate cluster quality and SPSS does not include any statistical tools to compare different models in cluster quality. When we checked the model for 5 clusters in more detail, we found that the clustering solution was substantially similar in many respects to the LPA model executed by Mplus (figure available upon request). The reasons why the models (profiles/clusters) were not fully identical may relate to various issues (e.g., caused by different estimator method as SPSS uses maximum likelihood [ML], but we used maximum likelihood robust [MLR] in LPA as we wanted to take into account the skewness of variables). For these reasons, we trust the results obtained via LPA. Furthermore, LPA is superior over cluster analysis as it allows a statistical comparison of the number of profiles/classes, and therefore it is nowadays a highly recommended (person-centered) analysis method in occupational/organizational psychology (see Spurk et al., 2020; Woo et al., 2018). Naturally, choosing the most adequate profile solution should also be based on theoretical models and/or earlier findings, and here we relied on cognitive load theory (Sweller, 1988) and transactional stress theory (Lazarus & Folkman, 1984). Furthermore, profile validity in our study was evaluated in terms of criterion validity (see Spurk et al., 2020), as we also explored whether and how profiles found were related to well-being indicators in theoretically meaningful ways. These findings are discussed next.

Implications of experiencing MJDs

We further validated the profile solution by testing how the profiles of MJDs differed in certain employee outcomes (i.e., job burnout, job performance, and meaning of work). The profiles should show meaningful differences in these outcomes to have sufficient criterion validity (Spurk et al., 2020). Indeed, risky profiles of MJDs should implicate negative outcomes, as has been predicted in the well-known job stress models (Karasek & Theorell, 1990; Siegrist, 1996). Overall, the results of SEM analyses validated the profile solution as the profiles were related to the selected employee outcomes in the directions anticipated. Nevertheless, there were also differences between the profiles in these relationships (either in direction or in magnitude) indicating that the profiles are also distinct with diverse implications.

Specifically, our second hypothesis proposed that employees belonging to high MJDs profile(s) form a risk group and are likely to report more burnout, poorer performance, and lower meaning of work (negative outcomes). The results of SEM analyses partly supported this hypothesis as the profile scoring high on all five MJDs (HMD profile) was associated with more job burnout (exhaustion and cynicism). However, this profile did not differ significantly from certain other profiles when job performance and meaning of work were analyzed as dependent variables, although belonging to this high MJDs profile predicted poorer job performance and meaning of work. These results are consistent with those of earlier studies, which have already shown that IJDs, illegitimate tasks, and interruptions at work are severe job stressors implying higher strain, e.g., job burnout, anxiety or psychosomatic symptoms (e.g., Eatough et al., 2016; Fletcher et al., 2017; Kubicek et al., 2015; Liebl et al., 2012; Semmer et al., 2015; Mauno et al., 2019b; Mauno et al., 2020). Nevertheless, in contrast to our study, these prior studies have analyzed these MJDs separately, ignoring combinations of them (profiles) and their outcomes, which we focused on.

Interestingly, SEM analyses further showed that belonging to other MJD profiles was also linked to negative outcomes. For example, the profile characterized by moderately high IJDs and moderate interruptions at work (MHIJD profile) also predicted more job burnout and impaired job performance. It is noteworthy that almost 30% of the participants belonged to this profile. Thus, even moderately high IJDs together with interruptions at work seem to include an elevated risk of harmful consequences and actuality concern quite a large number of employees.

Furthermore, profiles characterized by low learning demands and moderate other MJDs (LLD profile) also predicted more job burnout, poorer job performance, and perceiving one's work as less meaningful. Almost 20% of the participants belonged to this group. This latter finding suggests that MJDs without work-related learning demands may be a harmful combination too. MJDs require mental effort of an employee (e.g., Galy et al. 2012; Hancock and Matthews 2018; Kubicek et al. 2015; Zapf et al. 2014), and viewed from this angle it is possible that absence of learning alternatives may be detrimental, as learning opportunities could constitute a resource helping workers to cope with MJDs. Research has shown that learning demands at work are associated with positive outcomes (Glaser et al., 2015; Brem et al., 2017), but may also turn into stressors with negative implications if they are too high or too low (Mauno et al., 2019b; Mauno et al., 2020). However, it is also good to recall that there are very likely individual differences in needs/preferences for learning demands. Overall learning demands turned out to be a bit different job demand compared to other MJDs studied here and would need more attention in subsequent job stress studies.

Limitations and suggestions for future research

There are a few noteworthy limitations in our study. *First*, the design was cross-sectional, which did not allow testing temporal order between MJDs and employee outcomes, nor exploring changes in latent profiles or in their outcomes over time. A related point is that person-centered analysis methods best fit longitudinal studies, where we can for example can explore typical and atypical (individual) patterns of human development over time (e.g., Bergman & Lundh, 2015). However, nowadays person-centered analyses are common also in work and organizational psychology (Spurk et al., 2020; Woo et al., 2018).

Second, all data were collected via self-report, which may be problematic, particularly in assessing job performance (one of the outcomes studied). However, appraising environmental factors such as MJDs as stressors include also individual differences and cannot be assessed solely objectively (e.g., Brem et al., 2017; Lazarus & Folkman, 1984). To conclude, future studies on MJDs should apply longitudinal design and use also other measures than self-reports, such as objective performance indicators, as outcomes. Also, mediators and/or moderators (e.g., coping strategies) could be studied more reliably in longitudinal designs.

Third, the response rate was low except for upper-white collar workers (48%), which may have biased the findings at some extent. Furthermore, women and older employees were over-represented in certain subsamples. Maybe they considered the topic of survey more interesting (MJDs and well-being). A related point is that we cannot know how representative the samples are concerning the studied phenomena, e.g., whether those who are most (or least) stressed dropped out. However, overall the sample size was large and diverse (including both blue- and white-collar workers) allowing a reasonable statistical power and a fruitful basis for identifying diversity in the profiles of MJDs. Moreover, it should be recalled that LPA is a data driven method, and in this respect, it is often hard to predict what sorts of profiles will emerge from the data. Indeed, generalizability of the profiles may be limited, although the aim of person-centered analyses (e.g., LPA) is rather to understand how the phenomena of interest (here MJDs) would co-emerge at within- and between-levels than to produce generalizable profiles. However, it is also important to analyze criterion variables (here employee outcomes) in relation to profiles in order to indicate their criterion/predictive validity and their correspondence to theoretical models (here job stress models) (Spurk et al., 2020). The profiles identified in this study and in a given context (Finland) should be studied in different contexts (e.g., outside Scandinavia) using person-centered analytical methods. It would be also worth studying whether the profiles found here are time-invariant in a longitudinal design.

Fourth, the assessment of MJDs was not equal across

scales. Respondents rated perceived changes in IJDs occurring during the past five years (see Kubicek et al., 2015), whereas illegitimate tasks and interruptions at work were assessed based on the currently prevailing situation (not in relation to changes). IJDs aim to capture the phenomena of social and technological acceleration at work (Rosa, 2003), which is a slower societal process, and for this reason a five-year timeframe was used. This may prove problematic, particularly in follow-up data collection (if the time lag is less than five years).

Fifth, we tried to measure a wide spectrum of MJDs, which we expected to arise from ongoing technological and social acceleration as well from other structural changes in working life (e.g., Chesley, 2014; Galy et al., 2012; Green, 2004; Kubicek et al., 2015; Rosa, 2003). We can by no means be sure, however, that these MJDs tell us the whole story about the most relevant mental job demands in contemporary working life. Consequently, researchers and developers should be very sensitive to ongoing trends in working life by developing new concepts and scales to capture the most salient work demands.

Conclusions

As high and even moderately high MJDs implied more job burnout, poorer job performance, and also perceiving one's work to be less meaningful, MJDs should either be reduced, or employees should be provided with appropriate coping resources to help in managing MJDs. It is also crucial to realize that to some extent MJDs tend to co-occur within a person, meaning that employees experiencing one demand are more prone also to experience other demands. Thus, reducing MJDs would be helpful if they tend to accumulate. One way is to reduce the number of illegitimate tasks at work (unnecessary and unreasonable tasks; see Semmer et al., 2015), or "extra tasks" which employees perceive to be incompatible with their work roles or identities or which are just a waste of time. Of the five MJDs studied, this was most marked in the profile characterized by high MJDs and would therefore need particular sensitivity in job stress interventions. Organizations should pay more attention to core and peripheral tasks, especially as ongoing technological acceleration may increase the latter, at least in this early stage, before the systems and processes become more developed and user-friendly for employees. In the long run, advanced machine learning and artificial intelligence may even reduce illegitimate tasks. Regarding these conclusions, it should be recalled that the response rate was low in our study, and women and older employees were over-represented in certain subsamples. This, in turn, would suggest that these recommendations may concern better women and older employees.

Finally, even though buffering coping resources were beyond the scope of the present study, they may be helpful in coping with MJDs, a proposition which is also consistent with job stress models (e.g., Bakker & Demerouti, 2017;

Karasek & Theorell, 1990). As MJDs by definition require mental effort at work, mental recovery would be one functional coping resource. Accordingly, it would be wise to detach oneself mentally from work while not working and to maintain sufficient boundaries between work and non-work time and spheres (e.g., Sonnentag et al., 2017; Mauno et al., 2017; Mauno et al., 2019a). Moreover, a recent study found that those employees who perceived less intensified job demands (e.g., work intensification, intensified planning- and decision-making demands) reported greater supervisory support (Mauno et al., 2019a). Thus, managerial support, in different forms, could be one crucial organizational resource in mentally more demanding working life.

Declaration of interests

The authors declare that there is no conflict of interest, real and perceived, for any of the named authors.

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Author contributions

SM has been leading the research project related to this particular study and she was responsible for designing this study, and she also wrote the introduction and discussion. JM performed all statistical analyses and reported the results and methods.

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References

- Asparouhov, T., & Muthén, B. (2018). Auxiliary variables in mixture modeling: Using the BCH method in Mplus to estimate a distal outcome model and an arbitrary secondary model. Mplus Web Notes: No. 21 (version 3). Retrieved from <https://www.statmodel.com/examples/webnotes/webnote21.pdf>
- Bakker, A. B., & Demerouti, E. (2017). Job demands-resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology, 22* (3), 273–285. <https://doi.org/10.1037/ocp0000056>
- Bauer, D. J., & Curran, P. J. (2003). Distributional assumptions of growth mixture models: Implications for overextraction of latent trajectory classes. *Psychological Methods, 8*(3), 338–363. <https://doi.org/10.1037/1082-989X.8.3.338>
- Bergman, L. R., & Lundh, L.-G. (2015). Introduction: The person-oriented approach: roots and roads to the future. *Journal of Person-Oriented Research, 1* (1-2), 1–6. <https://doi.org/10.17505/jpor.2015.01>
- Brem, R., Ohly, S., Kubicek, B., & Korunka, C. (2017). Thriving or challenge stressors? Exploring time pressures and learning demands as antecedents of thriving at work. *Journal of Organizational Behavior, 38*, 108–123. <https://doi.org/10.1002/job.2115>
- Campbell, J. P. (1990). Modeling the performance prediction problem in industrial and organizational psychology. In M. D. Dunnette, & L. M. Hough (Eds.), *Handbook of Industrial and Organizational Psychology* (pp. 687–732). Palo Alto, CA: Consulting Psychologists Press, Inc.
- Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification, 13*, 195–212. <https://doi.org/10.1007/BF01246098>
- Chesley, N. (2014). Information and communication technology use, work intensification and employee strain and stress. *Work, Employment and Society, 28*(4), 589–610. <https://doi.org/10.1177/0950017013500112>
- Dillard, M. B., Warm, J. S., Funke, G. J., Nelson, W. T., Finomore, V. S., McClernon, C. K., et al. (2019). Vigilance tasks: Unpleasant, mentally demanding and stressful even when time flies. *Human Factors, 61*(2), 225–242.
- Eatough, E. M., Meier, L. L., Igc, L., Elfering, A., Spector, P. E., & Semmer, N. K. (2016). You want me to do what? Two daily diary studies of illegitimate tasks and employee well-being. *Journal of Organizational Behavior, 37*, 108–127. <https://doi.org/10.1002/job.2032>
- Feldt, T., Rantanen, J., Hyvönen, K., Mäkikangas, A., Huhtala, M., Pihlajasaari, P., et al. (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>
- Fletcher, K. A., Potter, S. M., & Telford, B. N. (2018). Stress outcomes of four types of perceived interruptions. *Human Factors, 60*(2), 222–235. <https://doi.org/10.1177/0018720817738845>
- Franke, F. (2015). Is work intensification extra stress? *Journal of Personnel Psychology, 14*(1), 17–27. <https://doi.org/10.1027/1866-5888/a000120>
- Galy, E., Cariou, M., & Melan, C. (2012). What is the relationship between mental workload factors and cognitive load types? *International Journal of Psychophysiology, 83*, 269–275. <https://doi.org/10.1016/j.ijpsycho.2011.09.023>
- Glaser, J., Seubert, C., Hornug, S., & Herbig, B. (2015). The impact of learning demands, work-related resources, and job stressors on creative performance and health. *Journal of Personnel Psychology, 14*, 37–48. <https://doi.org/10.1027/1866-5888/a000127>
- Green, F. (2004). Work intensification, discretion, and the decline in well-being at work. *Eastern Economic Journal, 30*(4), 615–625.
- Hancock, P. A. (2017). On the nature of vigilance. *Human Factors, 59*(1), 35–43. <https://doi.org/10.1177/0018720816655240>
- Hancock, P. A., & Matthews, G. (2018). Workload and performance: Associations, insensitivities, and dissociations. *Human Factors, 61*(3), 374–392. <https://doi.org/10.1177/0018720818809590>
- Jett, Q., R., & George, J. M. (2003). Work interrupted: A closer look at the role of interruptions in organizational life. *Academy of Management Review, 28*(3), 494–507. <https://doi.org/10.2307/30040736>

- Karasek, R. A., & Theorell, T. (1990). *Healthy work, stress, productivity and the reconstruction of working life*. New York, NY: Basic Books.
- Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling* (3th ed.). New York: The Guilford Press.
- Koopmans, L., Bernaards, C. M., Hildebrandt, V. H., Lerner, D., de Vet, H. C., & van der Beek, A. J. (2016). Cross-cultural adaptation of the Individual Work Performance Questionnaire. *Work*, 53(3), 609–619. <https://doi.org/10.3233/WOR-152237>
- Korunka, C., Kubicek, B., Paškvan, M., & Ulferts, M. (2015). Changes in work intensification and intensified learning: Challenge or hindrance demands? *Journal of Managerial Psychology*, 30(7), 786–800. <https://doi.org/10.1108/JMP-02-2013-0065>
- 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>
- Laursen, B. P., & Hoff, E. (2006). Person-centered and variable-centered approaches to longitudinal data. *Merrill-Palmer Quarterly*, 52(3), 377–389.
- Lazarus, R. & Folkman, S. (1984). *Stress, appraisal, and coping*. New York, NY: Springer.
- Liebl, A., Haller, B., Jödicke, H., Baumgartner, S., Schlittmeier, J., & Hellbrück, J. (2012). Combined effects of acoustic and visual distraction on cognitive performance and well-being. *Applied Ergonomics*, 43(2), 424–434. <https://doi.org/10.1016/j.apergo.2011.06.017>
- Lin, B. C., Kain, J. M., & Fritz, C. (2013). Don't interrupt me! An examination of the relationship between intrusions at work and employee strain. *International Journal of Stress Management*, 20(2), 77–94. <https://doi.org/10.1037/a0031637>
- Ma, J., & Peng, Y. (2019). The performance costs of illegitimate tasks: The role of job identity and flexible role orientation. *Journal of Vocational Behavior*, 110, 144–154. <https://doi.org/10.1016/j.jvb.2018.11.012>
- Mauno, S., Ruokolainen, M., De Bloom, J., & Kinnunen, U. (2017). Does recovery buffer against emotional labor in terms of motivational outcomes at work? Analyzing age differences among Finnish health care professionals. *Applied Nursing Research*, 36, 88–94. <https://doi.org/10.1016/j.apnr.2017.06.007>
- Mauno, S., Kubicek, B., Minkkinen, J., & Korunka, C. (2019a). Antecedents of intensified job demands: evidence from Austria. *Employee Relations*, 41(4), 694–707. <https://doi.org/10.1108/ER-04-2018-0094>
- Mauno, S., Minkkinen, J., Tsupari, H., Huhtala, M., & Feldt, T. (2019b). Do older employees suffer more from work intensification and other intensified job demands? Evidence from upper white-collar workers. *Scandinavian Journal of Work and Organizational Psychology*, 4(1): 3, 1–13. <https://doi.org/10.16993/sjwop.60>
- Mauno, S., Kubicek, B., Feldt, T., & Minkkinen, J. (2020). Intensified job demands and job performance: Does SOC strategy use make a difference? *Industrial Health*, 58(3), 224–237. <https://doi.org/10.2486/ind>
- Maslach, C., Schaufeli, W. B., & Leiter, M. P. (2001). Job burnout. *Annual Review of Psychology*, 52(1), 397–422.
- Mustosmäki, A. (2017). The intensification of work. In Tammelin, M (Ed.), *Family, work and well-being: emergence of new issues* (pp. 77-91). Switzerland: Springer.
- Muthén, B. O. (2001). Latent variable mixture modeling. In G. A. Marcoulides, & R. E. Schumacker (Eds.), *New developments and techniques in structural equation modeling* (pp. 1–33). Mahwah, NJ: Lawrence Erlbaum Associates.
- Muthén, B., & Muthén, L. K. (2000). Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research*, 24, 882–891. <https://doi.org/10.1097/0000374-200006000-00020>
- Muthén, L. K., & Muthén, B. O. (1998–2017). *Mplus User's Guide*. Eighth Edition. Los Angeles, CA: Muthén & Muthén.
- Nylund, K., Asparouhov, T., & Muthén, B. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, 14(4), 535–569. <https://doi.org/10.1080/10705510701575396>
- Paškvan, M., Kubicek, B., Prem, R., & Korunka, C. (2016). Cognitive appraisal of work intensification. *International Journal of Stress Management*, 23(2), 124–146.
- Rosa, H. (2003). Social acceleration: Ethical and political consequences of a desynchronized high-speed society. *Constellations*, 10, 3–33. <https://doi.org/10.1111/1467-8675.00309>
- Rosso, B. D., Dekas, K. H., & Wrzesniewski, A. (2010). On the meaning of work: A theoretical integration and review. *Research in Organizational Behavior*, 30, 91–127. <https://doi.org/10.1016/J.RIOB.2010.09.001>
- Salmela-Aro, K., Rantanen, J., Hyvönen, K., Tilleman, K., & Feldt, T. (2011). Bergen Burnout Inventory: Reliability and validity among Finnish and Estonian managers. *International archives of occupational and environmental health*, 84(6), 635–645. <https://doi.org/10.1007/s00420-010-0594-3>
- Sander, E., Caza, A., & Jordan, P. J. (2019). Psychological perceptions matter: Developing the reactions to the physical work environment scale. *Building and Environment*, 148, 338–347. <https://doi.org/10.1016/j.buildenv.2018.11.020>
- Seddigh, A., Berntson, E., Danielson, C. B., & Westerlund, H. (2014). Concentration requirements modify the effect of office type on indicators of health and performance. *Journal of Environmental Psychology*, 38, 167–174. <https://doi.org/10.1016/j.jenvp.2014.01.009>
- Semmer, N. K., Tschan, F., Meier, L. L., Facchin, S., & Jacobshagen, N. (2010). Illegitimate tasks and counterproductive work behavior. *Applied Psychology*, 59(1), 70–96. <https://doi.org/10.1111/j.1464-0597.2009.00416.x>
- Semmer, N. K., Jacobshagen, N., Meier, L. L., Elfering, A., Beehr, T. A., Kälin, W., et al. (2015). Illegitimate tasks as a source of stress. *Work & Stress*, 29(1), 32–56. <https://doi.org/10.1080/02678373.2014.1003996>
- Siegrist, J. (1996). Adverse health effects of high-effort/low-reward conditions. *Journal of Occupational Health Psychology*, 1(1), 27–41.

<https://doi.org/10.1037/1076-8998.1.1.27>

- Sonnentag, S., Venz, L., & Casper, A. (2017). Advances in recovery research: What have we learned? What should be done next? *Journal of Occupational Health Psychology, 22*(3), 365–380. <https://doi.org/10.1037/ocp0000079>
- Spurk, D., Hirschi, A., Wang, M., Valero, D., & Kauffeld, S. (2020). Latent profile analysis: A review and “how to” guide of its application within vocational behavior research. *Journal of Vocational Behavior* (online first). <https://doi.org/10.1016/j.jvb.2020.103445>
- Steger, M. F., Dik, B. J., & Duffy, R. D. (2012). Measuring meaningful work: The Work and Meaning Inventory (WAMI). *Journal of Career Assessment, 20*(3), 322–337. <https://doi.org/10.1177/1069072711436160>
- Sweller, J. (1988). Cognitive load theory during problem solving: effects on learning. *Cognitive Science, 12*, 257–285. https://doi.org/10.1207/s15516709cog1202_4
- Tabachnick, B. G. & Fidell, L. S. (2013). *Using Multivariate Statistics (6th Ed.)*. Boston, MA: Pearson Education.
- Tein, J-Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in latent profile analysis. *Structural Equation Modeling: A Multidisciplinary Journal, 20*(4), 640–657. <https://doi.org/10.1080/10705511.2013.824781>
- Warm, J. S., Parasuraman, R., & Matthews, G. (2008). Vigilance requires hard mental work and is stressful. *Human Factors, 50*(3), 433–441. <https://doi.org/10.1518/001872008X312152>
- Woo, S. E., Jebb, A. T., Tay, L., & Parrigon, S. (2018). Putting the “person” in the center: Review and synthesis of person-centered approaches and methods in organizational science. *Organizational Research Methods, 4*, 814–845. <https://doi.org/10.1177/1094428117752467>
- Zapf, D., Semmer, N., & Johnson, S. (2014). Qualitative demands at work. In Peeters, M., de Jonge, J., & Taris, T. (Eds.), *An introduction to contemporary work psychology* (pp. 144-169). Chichester, UK: Wiley Blackwell.

