Journal of Occupational Health Psychology

Testing Job Typologies and Identifying At-Risk Subpopulations Using Factor Mixture Models

Anita C. Keller, Ivana Igic, Laurenz L. Meier, Norbert K. Semmer, John M. Schaubroeck, Beatrice Brunner, and Achim Elfering

Online First Publication, April 25, 2016. http://dx.doi.org/10.1037/ocp0000038

Journal of Occupational Health Psychology

1076-8998/16/$12.00 http://dx.doi.org/10.1037/ocp0000038

Testing Job Typologies and Identifying At-Risk Subpopulations Using Factor Mixture Models

Anita C. Keller
Michigan State University

Ivana Igic
University of Bern

Laurenz L. Meier
University of Fribourg

Norbert K. Semmer
University of Bern

John M. Schaubroeck
Michigan State University

Beatrice Brunner
Zurich University of Applied Sciences

Achim Elfering
University of Bern

Research in occupational health psychology has tended to focus on the effects of single job characteristics or various job characteristics combined into 1 factor. However, such a variable-centered approach does not account for the clustering of job attributes among groups of employees. We addressed this issue by using a person-centered approach to (a) investigate the occurrence of different empirical constellations of perceived job stressors and resources and (b) validate the meaningfulness of profiles by analyzing their association with employee well-being and performance. We applied factor mixture modeling to identify profiles in 4 large samples consisting of employees in Switzerland (Studies 1 and 2) and the United States (Studies 3 and 4). We identified 2 profiles that spanned the 4 samples, with 1 reflecting a combination of relatively low stressors and high resources (P1) and the other relatively high stressors and low resources (P3). The profiles differed mainly in terms of their organizational and social aspects. Employees in P1 reported significantly higher mean levels of job satisfaction, performance, and general health, and lower means in exhaustion compared with P3. Additional analyses showed differential relationships between job attributes and outcomes depending on profile membership. These findings may benefit organizational interventions as they show that perceived work stressors and resources more strongly influence satisfaction and well-being in particular profiles.

Keywords: job stressors, job resources, well-being, performance, factor mixture model

Supplemental materials: http://dx.doi.org/10.1037/ocp0000038.supp

Theory and empirical research in occupational health psychology have shown that poor work quality affects employee well-being, health, and performance (Findlay, Kalleberg, & Warhurst, 2013; Humphrey, Nahrgang, & Morgeson, 2007; Sonnentag & Frese, 2012). A body of research has investigated the effects of job stressors and job resources on employees, showing that job stressors mostly have harmful effects, while job resources often have positive effects (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001; Humphrey et al., 2007; Sonnentag & Frese, 2012). Studies typically examine each type of situational characteristic (e.g., organizational constraints) as a separate variable, often controlling for the influence of other variables. Such an approach, however, does not account for constellations of job stressors and job resources that employees experience as hindering or enabling their strivings at work. For example, even though organizational constraints have a negative effect on employee well-being and per-

Anita C. Keller, Department of Psychology, Michigan State University; Ivana Igic, Department of Psychology, University of Bern; Laurenz L. Meier, Department of Psychology, University of Fribourg; Norbert K. Semmer, Department of Psychology, University of Bern; John M. Schaubroeck, Broad College of Business and Department of Psychology, Michigan State University; Beatrice Brunner, Winterthur Institute of Health Economics, Zurich University of Applied Sciences; Achim Elfering, Department of Psychology, University of Bern.

The research reported in this article was supported by the Swiss Health Promotion Foundation and the Swiss National Science Foundation (P2BEPI_158962). The funding sources had no involvement in analysis and interpretation of data, in the writing of the report, or in the decision to submit the article for publication.

Correspondence concerning this article should be addressed to Anita C. Keller, Department of Psychology, Michigan State University, 315 Psychology Building, East Lansing, MI 48824. E-mail: keller97@msu.edu

formance (Gilboa, Shirom, Fried, & Cooper, 2008; Pindek & Spector, 2016), such constraints may not produce the same harmful effects among employees with more resources. While various studies have also investigated the effects of moderators, these studies have tended to focus on specific factors in isolation. Moreover, they have tended to be limited in scope, because higher order interactions are even more difficult to detect than two-way interactions (McClelland & Judd, 1993), and if they do occur, analyses with more than two moderators are difficult to interpret.

While the variable-centered approach has proven useful in identifying work-related attributes that influence employee outcomes, we introduce a new approach to occupational health psychology that clusters employees based on their levels of perceived job stressors and resources. Theories of job stress have proposed that job attributes that are either stressful or promote coping can be distinguished more effectively by considering them as constellations of job attributes (Bakker & Demerouti, 2007; Karasek, 1979; Siegrist, 1996). However, such theories have generally proposed predefined lists of job attributes and predefined constellations of these attributes. In this study, we utilize factor mixture models (FMMs) to identify subgroups of employees who experience similar combinations of job stressors and resources, combining confirmatory factor analysis (CFA) with latent profile analysis (LPA). This approach helps to refine occupational health theories and enable occupational health psychology researchers to ascertain meaningful differences between work populations in terms of constellations of interest. Among its potential uses, this approach may enable organizational practitioners to target interventions in ways that may have greater salutary impact for a larger portion of employees than is possible by focusing on single variables (Semmer, 2006). Because factor mixture modeling represents an exploratory approach, it is important to cross-validate findings. We assessed four large samples: two samples consisting of Swiss employees and the other two of employees in the United States (U.S.). To examine each profile's criterion validity, we also assessed the relationships of these profiles with job satisfaction, exhaustion, general health, and subjective performance ratings.

Typologies of Job Stressors and Resources

Within the occupational health psychology literature, job attributes are often categorized as either job stressors or job resources. Job stressors, such as time pressure or performance constraints, refer to perceived attributes that are seen to demand coping responses and are therefore associated with certain costs. Job resources may serve to either reduce job stressors or support employees in coping with those stressors. Job resources also play a functional role in achieving work goals and stimulating personal growth and learning. Examples of job resources are job control and supervisory support (Bakker, Hakanen, Demerouti, & Xanthopoulou, 2007; Demerouti et al., 2001; Karasek, 1979).

The idea that certain constellations of job attributes capture unique and useful information is inherent in influential theories of work-related stress (Karasek, 1979; Siegrist, 1996). Among these theories, Karasek's (1979) job demands–control (JDC) model has been the most influential for research on occupational health and well-being. The JDC model states that high job stressors are not harmful, provided that job control—the employee's ability to influence and decide on tasks, methods, and means—is high. Karasek proposed four combinations of working conditions: (a) active jobs, which are characterized by high control and high demands; (b) high-strain jobs, which are characterized by low control and high demands; (c) passive jobs, which are characterized by low control and low demands; and (d) low-strain jobs, which are characterized by high control and low demands (Karasek, 1979; Karasek & Theorell, 1990). The JDC model assumes that active jobs promote well-being among employees because they are challenging (i.e., high potential for learning and growth), and high control provides resources to cope with the demands. High-strain jobs, on the other hand, were hypothesized to promote lower levels of well-being. In such jobs, employees are posited to lack the resources they need to cope with the high demands. Employees in the remaining two combinations of job demands and job control (passive jobs and low-strain jobs) report low demands. However, this also implies that they encounter fewer challenges and limited opportunities for development, which may lead to moderate or low levels of well-being (Karasek, 1979).

Other well-recognized theories of occupational stress have also discussed the effects of specific constellations. For example, the job demands-resources (JD-R) model generalizes the idea of constellations to various job resources in addition to job control (Bakker & Demerouti, 2007), and the effort-reward imbalance (ERI) model describes high effort combined with low rewards as a specific constellation that causes strain (Siegrist, 1996).

For a number of reasons, one could expect that employees' experience of work goes beyond the theoretically proposed types of constellations. Accordingly, some arguments can be made with respect to the comprehensiveness of the theoretical models. First, the typology of exactly four combinations of attributes proposed by the JDC and JD-R models may not reflect employees' overall experiences of work. Considerable evidence from cognitive psychology supports theories concerning how people organize their experiences. According to cognitive categorization theory, people use categories to process the complexity of the world in a cognitively economical manner (Mervis & Rosch, 1981; Rosch & Mervis, 1975). Cognitive categorization theory has contributed to a general understanding in psychology that individuals base judgments, beliefs, and actions on holistic conceptions of attributes, theories about the world, goals, and information related to the category as a whole (Goldstone, 1994). For example, employees may assign their job attributes to different categories in order to inform themselves about appropriate and successful behavior in the workplace. The attributes individuals organize into categories interrelate in distinct ways. Some attributes tend to coalesce in pairs, some cannot occur together, and some rarely or never appear in a category. Attributes can be unique to one category or shared across several categories (e.g., Porac & Thomas, 1994). Rosch and colleagues observed that not all hypothetically possible combinations of attributes and categories appear in reality (Mervis & Rosch, 1981). There is some empirical support for this assumption. In one of the few studies investigating constellations of multiple job attributes, Holman (2013) found six empirical combinations of stressors and resources. However, he found that only three of the four constellations specified by Karasek (1979) were well represented in his working populations; there was no empirical evidence for "low-strain jobs."

Second, additional job stressors and job resources, especially social aspects of work, may refine constellations of job attributes.

Social aspects may relate to both stressors and resources. Social stressors, such as conflicts or animosities at work, may be especially toxic to employee health and well-being (Semmer, Jacobshagen, Meier, & Elfering, 2007; Spector & Bruk-Lee, 2008). For example, Bowling and Beehr (2006) found that workplace mistreatment had the greatest negative effect on employee well-being and health when compared with other job stressors. In a meta-analysis reported by Viswesvaran, Sanchez, and Fisher (1999), social resources, such as support from supervisors or colleagues, were found to moderate the relationship between stressors and strain and mitigate perceived stressors. This result supports Karasek and colleagues' extension of the JDC model in which they added social support as another resource that can help employees to deal with job stressors (Karasek, Triantis, & Chaudhry, 1982). Social support may also act as an important resource by fostering feelings of relatedness, positive self-evaluation, and a sense of competence (Dormann & Zapf, 2004; Semmer et al., 2007).

Third, constellations of attributes may appear in which single aspects of one's job may impact a wide range of one's subjective job experiences. For example, what may appear to be a low-strain job may be additionally characterized by a rather high mean level of time pressure. Consequently, the effect on employees may differ between the low-strain job and the low-strain job with high time pressure.

In sum, individuals likely use categories to reflect their job demands and resources, rather than considering their work in terms of several separate attributes. Thus, empirically derived constellations may extend the theoretical possibilities discussed so far in the literature.

Constellations of Job Stressors and Resources

Most studies of job attributes in occupational health psychology have investigated the effects of either a single job attribute (e.g., Bosma et al., 1997) or several job attributes combined into one or two factors (e.g., Schaufeli, Bakker, & Van Rhenen, 2009; Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2009). Typically, these studies have investigated the unique contribution of each variable (which may consist of scores, scales, and indices) to the variance explained in outcome variables. This approach, however, is based on mean relationships between job attributes and outcomes and does not account for individual variability. This notion of averaging results across an entire sample also applies to conventional analyses of moderation. Examining job stressors and resources in this way does not elucidate whether all job stressors are equally important to all employees or whether some stressors are especially relevant and harmful. In addition, moderators are statistically difficult to detect (Shieh, 2009); the results concerning postulated interaction effects are often inconclusive (Häusser, Mojzisch, Niesel, & Schulz-Hardt, 2010); and higher order interactions quickly become difficult to interpret, even if they are appropriate for reflecting the complexity of work experience.

To investigate the effects of different constellations of job attributes, some studies have used predefined subgroups. For example, researchers often use weighted scores of established scales and apply median or mean cut-off values based on studies that tested the scale with large (representative) samples (Tsai, Lai, Shih, Lin, & Liou, 2014) or median splits based on their own sample (as, e.g., in the Whitehall II studies, e.g., Elovainio et al., 2009). In these latter approaches, individuals are categorized according to the mean experiences of individuals who have been exposed to particular job attribute levels, rather than by their actual experiences. In reality, their actual experiences may differ markedly depending on the presence or absence of other attributes and individual differences.

In the present study, we use a person-centered approach to identify latent subgroups of employees. This approach is based on the assumption that there is both observed and unobserved heterogeneity in the population. Observed heterogeneity can be captured by predefined groups, such as the pairs of attribute levels often used in testing the JDC model, or moderator analyses. A person-centered approach identifies subgroups of individuals who are similar to each other, yet different from individuals in other subgroups (Clark et al., 2013; Jedidi, Jagpal, & DeSarbo, 1997). This approach seeks to identify the most common ways employees differ in their experience of job demands and resources.

In sum, the person-centered approach has several benefits. First, it allows researchers to identify common ways in which employees characterize their work experiences, rather than relying upon strictly theoretical categorizations. Second, it may enable researchers to gain more comprehensive knowledge as to which job attributes are more relevant to large subgroups of employees, and to identify the particular subgroups for which interventions such as job redesign would be most beneficial. Third, this approach can identify unobservable moderating factors (as reflected in subgroup membership) that can account for heterogeneity among employees.

These considerations suggest the following research question:

> *Research Question 1:* Are combinations of theoretically distinct job stressors and job resources represented in empirical constellations? If so, how can these constellations be characterized?

Validation of Profiles

Once job attribute profiles have been identified, validation is required to determine whether they contribute meaningfully to understanding individuals' experiences (Bauer & Curran, 2004). Generally, job stressors have negative linear relationships with indices of positive well-being (e.g., general health) and positive relationships with indices of negative well-being (e.g., exhaustion; for an overview see Sonnentag & Frese, 2012). Job stressors tend to create a mismatch between the work environment and what a person is able to cope with, which in turn leads to strain (French, Caplan, & Van Harrison, 1982) and lower levels of job satisfaction (Dawis & Lofquist, 1984). Job stressors require employees to dedicate additional mental and physical resources in order to fulfill their tasks. These additional costs may exhaust employees (Ilies, Dimotakis, & De Pater, 2010). If job stressors persist over longer periods of time, the activation level caused by the job stressors is maintained. In such cases, the stress experience becomes chronic and may affect the individual's ability to recover (e.g., Schaubroeck & Ganster, 1993). The ability to cope with demands then is compromised and health impairments become likely (Meijman & Mulder, 1998). In addition to instigating processes that deplete energy, job stressors may also act as situational constraints that hinder employees from fulfilling their tasks (e.g., organizational constraints, such as insufficient materials; Gilboa et al., 2008; Peters, O'Connor, Eulberg, & Watson, 1988; Pindek & Spector, 2016). Coping with job stressors requires employees to expend energy and time, and draws their attention away from their assigned tasks, thereby potentially lowering task performance (Jex, 1998).

Job resources exhibit patterns that are the obverse of those found for stressors (Humphrey et al., 2007; Sonnentag & Frese, 2012). Job resources such as job control support the achievement of work goals and the ability of the individual to cope with job stressors. Job resources have motivating potential (Hackman & Oldham, 1976) and may stimulate personal development (Xanthopoulou et al., 2009). Therefore, employees tend to intrinsically value job resources and perceive high resources as being positively associated with well-being (Humphrey et al., 2007). Job resources may increase the experience of meaningfulness, which tends to be positively associated with job performance (Hackman & Oldham, 1976; Humphrey et al., 2007) and their absence may also hinder effective performance (e.g., lack of time control causes employee to perform a task when fatigued instead of first taking a break). A lack of job resources, or the threat of losing them may have direct negative effects on performance, well-being, and health (Hobfoll, 1989; Schaufeli & Bakker, 2004).

With regard to constellations of job stressors and resources, research has often compared high-strain jobs with other types of jobs and confirmed that their incumbents experience lower well-being and poorer physical health than incumbents of the other types of jobs (e.g., De Lange, Taris, Kompier, Houtman, & Bongers, 2004; Schnall, Schwartz, Landsbergis, Warren, & Pickering, 1998). Thus, we might expect to find constellations that differ in terms of their favorability (meaning a lesser tendency to promote low well-being or low performance) with respect to these attributes.

In this study, we use well-being and self-rated performance to evaluate the meaningfulness of, and differences between, the empirically derived profiles of job attributes. The indicators include job satisfaction, exhaustion, general health, and performance ratings. Membership in a profile group is treated as a predictor of employee outcomes, and we assess the incremental variance explained by this predictor in conjunction with continuous measures of the separate job attributes that combine to form the profiles. While this is a conservative approach to validating profiles, it is in line with previous research that has combined person- and variable-centered techniques (e.g., Gabriel, Daniels, Diefendorff, & Greguras, 2015; Meyer, Stanley, & Vandenberg, 2013).

> *Research Question 2:* Are relationships between profiles and outcome variables consistent with theoretical assumptions? Are constellations characterized by higher levels of job stressors and lower levels of job resources associated with lower levels of job satisfaction, performance, and general health, and higher levels of exhaustion?

Method

We investigated the research questions in four population-based samples. Studies 1 and 2 consisted of Swiss, and Studies 3 and 4 of U.S. employees. Given that the categories of job stressors and resources beyond the JDC model lack explicit theoretical foundation (Sonnentag & Frese, 2012), we focused on job stressors and job resources that are in line with occupational stress theories and widely used to assess quality of work among employees, regardless of their specific job and occupation.

Participants

Studies 1 and 2. Data collection for Studies 1 and 2 took place in 2014 and 2015. The recruitment of participants was based on a large Internet panel. Participants in this panel were representative of the Swiss working population in terms of gender, age, education, and industry. The panel administrators recruited all participants by phone and invited them via e-mail to answer the online questionnaire. Participation was open to anyone who was working full- or part-time and not in vocational training. In Study 1, 3,497 participants completed the questionnaire. We excluded 59 individuals because response pattern and timing analyses indicated that they had either completed the questionnaire too quickly (total duration of less than 12 min or less than 10 s per page) or used only the extreme response options. For the purpose of the current study, we also excluded participants who reported having no supervisor (n = 410). Therefore, the final sample size for Study 1 was 3,028. In Study 2, 3,062 participants completed the questionnaire. Sixty-five participants were excluded through pattern and timing analyses, 153 participants were excluded due to missing values for gender, age, language, and economic sector, and 309 participants indicated having no supervisor. The final sample size for Study 2 was 2,535. In Studies 1 and 2, most participants had a vocational degree (Study 1: 42.8%; Study 2: 40.7%) or a university degree (bachelor's or master's; Study 1: 30.8%; Study 2: 32.1%). The most common sectors employees worked in were sales (Study 1: 13.3%; Study 2: 12.4%), health and welfare (Study 1: 12.3%; Study 2: 12.6%), construction (Study 1: 10.6%; Study 2: 10.6%), and production (Study 1: 10.8%; Study 2: 12.1%). Most participants (Study 1: 67.1%; Study 2: 66.2%) reported having a full-time contract (more than 38 hr a week). Participants reported working on average 38.3 hours (SD = 11.3) in Study 1 and 37.8 hours (SD = 11.2) in Study 2 per week. In Study 1 36.1% and in Study 2 32.0% of the participants reported holding a leadership position.

Studies 3 and 4. The General Social Survey (GSS) is conducted by the independent research institution NORC at the University of Chicago. It aims at monitoring social change in American society. The GSS uses full-probability sampling to select respondents from the adult, English-speaking (English and Spanish-speaking in 2006) population of the United States. As part of their 2002 and 2006 questionnaires, they assessed a variety of work attributes. In 2002 (Study 3), 2,765 individuals responded to the survey. We restricted our sample to individuals who were employed (exclusion of 96 participants), not self-employed (exclusion of 307 participants), worked more than eight hours a week, and indicated their occupation. This resulted in the exclusion of 890 participants in total. Another 82 participants were excluded because they had missing values on job characteristic indicators. The final sample for Study 3 consisted of 1,390 employees. In 2006 (Study 4), 4,307 individuals filled out the survey. We excluded 203 individuals because they were not employed, 508 because they were self-employed, and 1,492 because they did not indicate working more than eight hours a week or an occupation.

Another 1,008 participants had to be excluded because they had missing values on job characteristic indicators. The final sample of Study 4 consisted of 1,299 employees. In Studies 3 and 4, most participants were Caucasian (Study 3: 78.1% Caucasian, 15.4% African American; Study 4: 73.4% Caucasian, 16.3% African American), and most employees had graduated from high school (Study 3: 55.3%; Study 4: 49.4%) or held a bachelor's degree (Study 3: 18.3%; Study 4: 21.2%). Participants reported working a mean of 42.5 (SD = 12.9) hours per week in Study 3 and 42.6 (SD = 12.9) in Study 4.

Measures

Table 1 shows means, standard deviations, scale ranges, number of indicators, and Cronbach's alpha reliabilities for the study variables for each of the four studies.

Job stressors and job resources. Below we present job stressors and job resources according to the factor structure we established in the first step of our analyses. Value labels are available in the supplemental material. In Studies 1 and 2, measures of role uncertainty and performance constraints served as the indicators of organizational job stressors. For task-related stressors, the indicators were time pressure and qualitative overload. Social stressors were assessed using items relating to difficult interactions with supervisors and coworkers. Time pressure (four items, e.g., "How often do you have to finish work later because of having too much to do?"), role uncertainty (three items, e.g., "How often do you receive contradictory instructions from different supervisors?"), and performance constraints (four items, e.g., having to work with inadequate devices or obsolete information) were assessed using the Instrument for Stress-Oriented Task Analysis (ISTA; Semmer, Zapf, & Dunckel, 1995). Qualitative overload was assessed using three items from the Salutogenetic Subjective Work Analysis (SALSA; Udris & Rimann, 1999) questionnaire (e.g., "It happens that work is too difficult"). Social stressors (e.g., "I often quarrel with my boss") were assessed using eight items from the social stressors scale developed by Frese and Zapf (1987).

Job resources were indexed using measures of job control, task identity, support from supervisors, and recognition. Job control was assessed using five items from the ISTA (Semmer et al., 1995). Items focused on the degree of freedom one has to decide when (two items for time control, e.g., "To what extent are you able to plan your working day yourself?") and how to perform tasks at work (three items for method control, e.g., "Can you yourself decide which way to carry out your work?"). We measured task identity using an item from the SALSA (Udris & Rimann, 1999; "On my job I can produce something or carry out an assignment from A to Z"). Supportive behavior by supervisors was measured using four items (e.g., "The line manager lets one know how good a job one has done;" Udris & Rimann, 1999), and recognition was assessed using a single item (Stocker, Jacobshagen, Krings, Pfister, & Semmer, 2014).

In Studies 3 and 4, we used two items as indicators for organizational stressors (e.g., "I have enough information to get the job done") and two items as indicators for task-related stressors (e.g., "I have enough time to get the job done). Information on social stressors was not available in these two datasets. We used four indicators for task-related resources (e.g., "My job lets me use my skills and abilities") and three indicators for social support (e.g., "My supervisor is helpful to me in getting the job done").

Job satisfaction. In Studies 1 and 2, a single item ("In general, how satisfied are you with your current work situation?;" Baillod & Semmer, 1994) was used to measure job satisfaction. The response scale showed a dissatisfied (1= *downwards facing mouth*) to neutral (4 = *straight mouth*) to happy (7 = *upwards facing mouth*) face, so called smiley-faces (Kunin, 1955). In Studies 3 and 4, the item "All in all, how satisfied would you say you are with your job?" was used to assess job satisfaction.

Exhaustion. In Studies 1 and 2, the eight-item scale developed by Demerouti, Bakker, Nachreiner, and Schaufeli (2001) (e.g., "After my work, I usually feel worn out and weary") was used to measure exhaustion. In Studies 3 and 4, the item "How

Table 1
Means, Standard Deviations, and Cronbach's Alphas of Study Variables for the Four Studies

	Study 1: Switzerland 2014 (N = 3,028)					Study 2: Switzerland 2015 (N = 2,535)					Study 3: U.S. 2002 (N = 1,390)					Study 4: U.S. 2006 (N = 1,299)				
	Mean	SD	Range	#Ind	α	Mean	SD	Range	#Ind	α	Mean	SD	Range	#Ind	α	Mean	SD	Range	#Ind	α
Female (1)	.48	.50	0–1	1	—	.53	.50	0–1	1	—	.52	.50	0–1	1	—	.54	.05	0–1	1	—
Age	42.04	11.65	16–65	1	—	42.78	12.43	16–65	1	—	39.88	12.31	18–86	1	—	41.15	12.45	18–85	1	—
Part-time (1)	.33	.47	0–1	1	—	.34	.47	0–1	1	—	.15	.36	0–1	1	—	.13	.34	0–1	1	—
Private stressors	1.37	.41	1–4	4	.75	1.37	.40	1–4	4	.74	3.00	.89	1–4	1	—	3.00	.84	1–4	1	—
Organizational stressors	2.31	.68	1–5	7	.79	2.31	.68	1–5	7	.80	1.61	.63	1–4	2	.65	1.67	.64	1–4	2	.65
Task stressors	2.63	.67	1–5	7	.80	2.62	.65	1–5	7	.80	2.03	.66	1–4	2	.53	2.05	.64	1–4	2	.65
Social stressors	1.64	.66	1–5	10	.89	1.62	.66	1–5	10	.89	na	na	na	na	na	na	na	na	na	na
Task resources	3.75	.79	1–5	7	.83	3.70	.78	1–5	7	.83	3.20	.55	1–4*	4	.67	3.16	.56	1–4*	4	.67
Social resources	3.73	.82	1–5	6	.88	3.74	.79	1–5	6	.88	3.33	.65	1–4*	3	.70	3.29	.66	1–4*	3	.71
Job satisfaction	5.25	1.20	1–7	1	—	5.40	1.13	1–7	1	—	3.33	.74	1–4*	1	—	3.28	.75	1–4*	1	—
Exhaustion	2.09	.54	1–4	8	.82	2.06	.55	1–4	8	.84	3.35	1.13	1–5*	1	—	3.39	1.13	1–5*	1	—
General health	4.06	.73	1–5	1	—	4.08	.70	1–5	1	—	3.72	1.01	1–5*	1	—	3.67	1.01	1–5*	1	—
Performance	8.11	1.29	0–10	1	—	8.03	1.26	0–10	1	—	na	na	na	na	na	na	na	na	na	na

Note. SD = standard deviation; #Ind = number of indicators.
* In Studies 3 and 4, the response options for task resources, social resources, job satisfaction, exhaustion, and general health were reversed (see description of general health in Method section). We recoded these items for the purpose of this article. For clarity, intercorrelations of study variables are not shown here, but, along with more detailed descriptive statistics, are available from the first author.

often during the past month have you felt used up at the end of the day?” was used to assess exhaustion.

General health. In Studies 1 and 2, participants rated their general health (“How would you describe your general health?”). In Studies 3 and 4, we used a recoded version of the general health item (“Would you say that in general your health is excellent, very good, good, fair, or poor?”).

Subjective performance. In Studies 1 and 2, we used an item from the Work Performance Questionnaire (Kessler et al., 2003) to measure subjective performance. The item asked participants to estimate their average performance over the previous 12 months. Data on job performance were not available in Studies 3 and 4.

Control variables. In occupational health psychology literature, gender, age, part-time employment, and private stressors are discussed as relevant control variables because they can affect relationships between job attributes and well-being and performance (e.g., Guest, Oakley, Clinton, & Budjanovcanin, 2006; Ng & Feldman, 2008, 2014). We included these variables in the analyses of covariance (ANCOVAs) and the regression analyses reported here. We also ran all of the analyses without these control variables and obtained the same patterns. Participants in all four studies indicated their gender, age, and whether they worked full- or part-time. In Studies 1 and 2, we assessed *private stressors* using the four items from the family-to-work conflict scale (e.g., “You do not feel like working because of problems with your spouse/family/friends?”) developed by Geurts et al. (2005). In Studies 3 and 4, we used the item “How often do the demands of your family interfere with your work on the job?” to assess private stressors. In addition, personal resources such as self-efficacy may support employees in dealing with job stressors (Xanthopoulou, Bakker, & Demerouti, 2007). However, indicators for personal resources were only available in Studies 1 and 2. Because controlling for personal resources did not alter the relationships between profiles and outcome variables, we report the results for Studies 1 and 2 without controlling for personal resources.

Analytical Procedure

For this study, we applied factor mixture modeling. FMMs combine a common factor model and latent class models. Latent class or profile models are appropriate if the sample consists of different subtypes that are not known beforehand. The technique is used to cluster participants into subtypes in order to model the unobserved heterogeneity. With this technique, subpopulations are allocated to different profiles. Individuals are homogenous within a profile, but differ between profiles. Therefore, differences in the assessment of one’s work are attributed to one’s membership to a particular profile. In research on mental disorders, this approach is referred to as a categorical view, and there is a debate whether a dimensional view might be more appropriate. In the dimensional approach, continuous latent factors are used to represent underlying dimensions and the correlations among symptoms. The common factor model represents the theoretical concepts underlying the relationships between the measured indicators; it represents the factor structure for a homogeneous population. FMMs combine the categorical and dimensional views; the model allows researchers to categorize individuals into groups (categorical view) and allows for heterogeneity within groups through the latent factors (dimensional view; Clark et al., 2013; Lubke & Muthén, 2005).

We followed a hierarchical approach as outlined by Clark et al. (2013) to apply the FMMs to our data. First, we conducted a confirmatory factor analysis (CFA) to confirm the assumed underlying factor structure. In Studies 1 and 2, if the subdomain was measured by more than one item, we used factor means as item parcels. We used the parceling method described by Bagozzi and Edwards (1998) as a partial aggregation model and computed the average of the respective items of each subscale (e.g., performance constraints were represented by the mean of the four respective items). In Studies 3 and 4, we used item indicators for the FMMs. Results showed that our data reflected organizational, task-related, and social stressors and resources. Second, using the factor structure obtained, we estimated an increasing number of profile extractions and compared them with each other based on their model fit. However, as outlined by Clark et al. (2013), FMMs may reduce the number of factors and profiles needed. Therefore, we also investigated solutions with fewer factors (e.g., by combining organizational and task-related stressors) in order to determine whether a more parsimonious measurement would better fit the data.

We modeled factor loadings, intercepts, and residual variances to be equal across profiles. We compared these models with less constrained models by testing the release of equality constraints on the factor loadings across profiles (Clark et al., 2013). The results of these models tended to differ only in minor ways, but showed difficulties in the replication and estimation of Lo-Mendell-Rubin Adjusted Likelihood Ratio Test and Bootstrapped Likelihood Ratio Test. As stated by Lubke and Spies (2008), using moderate to large numbers of observed variables can result in difficulties estimating models with few constraints. The more constrained FMMs provide for more parsimonious models and ensure that job stressors and resources are represented the same way across classes (Lubke & Muthén, 2005; Meredith, 1993).

In order to compare model solutions and to determine the optimal number of profiles, we compared the models according to the following fit indices: Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMR; Lo, Mendell, & Rubin, 2001), Bootstrapped Likelihood Ratio Test (BLRT; Arminger, Stein, & Wittenberg, 1999; McLachlan & Peel, 2004), Akaike information criterion (AIC; Akaike, 1974), sample size-adjusted Bayesian information criterion (SSA-BIC; Schwarz, 1978), and entropy (Jedidi, Ramaswamy, & DeSarbo, 1993). The LMR and BLRT compare a k-class model to a k-1 model. The p values for the LMR and BLRT indicate whether the solution with more classes fits the data better, with significant p values indicating that a k-class model is preferable to a k-1-class model. It is important to note that LMR and BLRT compare a k-class model to a k-1-class model only for the same factor solution (Clark et al., 2013). For the AIC and SSA-BIC, which are descriptive fit indices, smaller values indicate better model fit. Entropy measures the precision of the latent class categorization (Jedidi et al., 1993); it ranges from 0 to 1, with higher values indicating better categorization. Entropy values around .80 or higher imply a suitable classification (Greenbaum, Del Boca, Darkes, Wang, & Goldman, 2005; Muthén, 2001). The LMR and BLRT are currently viewed as the most effective indices for deciding on the optimal number of classes (e.g., McLachlan & Peel, 2004). In the context of factor mixture modeling, the BIC, LMR, and BLRT indices may be the most appropriate for evaluating model fit (Clark et al., 2013). To reduce the danger of overextraction of classes, we only accepted model solutions if all three fit indices indicated that the solution was acceptable.

Factor mixture modeling was conducted using Mplus version 7 (Muthén & Muthén, 1998–2012). After identifying the model with the best fit, we assigned the latent class membership derived from the model to each participant. To validate the results (Research Question 2), we conducted a series of ANCOVAs to evaluate differences in outcome variables as a function of class membership. Post hoc analyses were performed using the Bonferroni correction. In addition, we analyzed whether classes continued to be significant predictors of outcomes after individual scale scores for job stressors, job resources, and the interaction between stressors and resources were incorporated into the regression analyses. Lastly, we performed regression analyses to assess the relative importance of different job stressors and resources within profiles for two exemplary outcomes. For the last two sets of analyses, we focused on job satisfaction and exhaustion because data were available for all four studies.

Results

Identifying Constellations: Factor Mixture Models

Table 2 shows fit statistics for all estimated profile solutions across the four studies. For Studies 1 and 2, BIC, LMR, and BLRT supported the extraction of three profiles. In terms of the best factor solution, the two studies differed. In Study 1 (Switzerland-2014), a four-factor solution resulted in the best model fit, whereas a five-factor solution exhibited the best fit in Study 2 (Switzerland-2015). For Studies 3 and 4 (U.S.), both samples supported a four-factor solution with two profiles. Across all four studies, quality of classification was good, with entropy ranging from .86 to .91. Table 3 and Figure 1 show mean values of job stressors and resources for the profiles across studies. Across the four studies, the identified profiles differed particularly in terms of organizational stressors and social aspects of work. Mean levels of task resources differed slightly, but did not show large differences between profiles. However, we found some differences between the Swiss (Studies 1 and 2) and U.S. (Studies 3 and 4) samples in terms of task stressors. In the Swiss samples (Studies 1 and 2), task stressors played a less important role in differentiating profiles. In Study 1 (Switzerland-2014), a model that combined organizational and task-related stressors exhibited a better fit to the data than a model that differentiated between these two types of stressors. In both U.S. samples (Studies 3 and 4), task-related stressors differed significantly between the two identified profiles. This difference was particularly pronounced in Study 3 (U.S.-2002), in which task-related stressors differed considerably between the two profiles, whereas social resources differed at a statistically significant level, but not to a very large extent. This pattern was reversed in Study 4 (U.S.-2006), in which social resources differed considerably between the two profiles, whereas the differences in terms of task stressors were not substantial.

In each of the four studies, we found one profile with relatively low stressors and high resources (labeled P1: low stressors—high resources) and one with relatively high stressors and low resources (labeled P3: high stressors—low resources). In Studies 1 and 2 (Switzerland), the data also suggested a third profile. In this profile

Table 2
Fit Statistics for Factor Mixture Models for the Four Studies

Number of profiles and factors	AIC	BIC	SSA-BIC	LMR (*p*)	BLRT (*p*)	Entropy
Study 1: Switzerland 2014						
2p-4f	65255.5	65502.1	65371.8	<.001	<.001	.91
2p-5f	65172.8	65449.5	65303.3	<.001	<.001	.91
3p-4f	**64755.5**	**65032.2**	**64886.1**	**<.001**	**<.001**	**.90**
3p-5f	64657.4	64970.2	64805.0	<.001	.68	.90
4p-4f	64458.0	64764.8	64602.7	<.001	.25	.90
4p-5f	64553.0	64902.0	64717.7	.10	.67	.86
Study 2: Switzerland 2015						
2p-4f	53854.7	54094.1	53963.8	<.001	<.001	.92
2p-5f	53772.8	54041.3	53895.2	<.001	<.001	.92
3p-4f	53466.3	53734.8	53588.7	<.001	.43	.90
3p-5f	**53385.6**	**53689.2**	**53524.0**	**<.001**	**<.001**	**.90**
4p-4f	53176.9	53474.7	53312.6	*	*	.90
4p-5f	53098.3	53436.9	53252.6	*	*	.90
Study 3: U.S. 2002						
2p-3f	32453.9	32663.4	32536.3	<.01	<.001	.87
2p-4f	**32315.6**	**32546.1**	**32406.3**	**<.001**	**<.001**	**.91**
3p-3f	32369.6	32600.0	32460.2	.29	<.001	.88
3p-4f	32190.1	32446.7	32291.1	.06	<.001	.89
Study 4: U.S. 2006						
2p-3f	30005.0	30211.8	30084.7	.07	<.001	.86
2p-4f	**29910.9**	**30138.3**	**29998.6**	**<.05**	**<.001**	**.86**
3p-3f	29966.2	30193.7	30053.9	.10	1.00	.86
3p-4f	29846.4	30099.7	29944.0	.07	1.00	.87

Note. xp = number of profiles; xf = number of factors; AIC = Akaike information criteria; BIC = Bayesian information criteria; SSA-BIC = sample-size-adjusted BIC; LMR = Lo, Mendell, and Rubin (2001) test; BLRT = bootstrapped log-likelihood ratio test. Solution with best model fit printed in bold.
* No reliable solution was found for this model because of failure to replicate.

Table 3
Means and Standard Deviations for Factors Across the Four Studies

	n	%	Org. stressors	Task stressors	Social stressors	Task resources	Social resources
Study 1 (N = 3,028)							
P1	2,218	73	2.35 (.75)		1.26 (.56)	3.87 (.85)	3.92 (.80)
P2	598	20	2.89 (.81)		2.42 (1.25)	3.53 (.88)	3.15 (1.15)
P3	212	7	3.28 (.73)		3.70 (1.08)	3.26 (.96)	2.26 (1.06)
Study 2 (N = 2,535)							
P1	1,878	74	2.21 (1.04)	2.94 (.87)	1.25 (.78)	3.84 (1.00)	3.94 (.91)
P2	465	18	2.84 (.64)	3.29 (.55)	2.40 (1.09)	3.44 (.61)	3.11 (.85)
P3	192	8	3.43 (1.34)	3.55 (1.38)	3.63 (1.66)	3.10 (1.55)	2.43 (1.42)
Study 3 (N = 1,390)							
P1	1,141	82	1.44 (.61)	1.50 (.61)	na	3.27 (.65)	3.38 (.81)
P3	249	18	1.90 (.79)	3.37 (.65)	na	3.16 (.73)	2.83 (.99)
Study 4 (N = 1,299)							
P1	1,129	87	1.49 (.67)	1.78 (.91)	na	3.37 (.84)	3.49 (.77)
P3	170	13	1.97 (.79)	2.42 (1.42)	na	2.97 (.91)	1.82 (2.02)

Note. Org. stressors = organizational stressors. In the first study, a four-factor solution fit best to the data (combination of organizational and task stressors); na = not available.

(labeled P2: mid stressors—mid resources), the mean levels of job stressors and resources were in between those of P1 and P3, and social stressors were high relative to the other profiles. The occurrence of a third profile may be due to certain social stressors being measured in Studies 1 and 2 (Switzerland), which were not available in Studies 3 and 4 (U.S.). Therefore, we conducted supplemental analyses excluding the social stressors in Studies 1 and 2 (Switzerland); results again demonstrated best model fit for the extraction of three profiles.

Most employees were classified into P1 (Study 1: 73%; Study 2: 74%; Study 3: 82%; Study 4: 87%). In the two Swiss samples, P2 was the second most common (Study 1: 20%; Study 2: 18%), and P3 the least common (Study 1: 7%; Study 2: 8%). In the two studies based on U.S. employees (Studies 3 and 4), 18% (Study 3), and 13% (Study 4) were classified into P3. For all four studies, post hoc ANCOVA tests (performed using SPSS 22) showed that the mean values of job stressors and job resources differed significantly across the profiles.

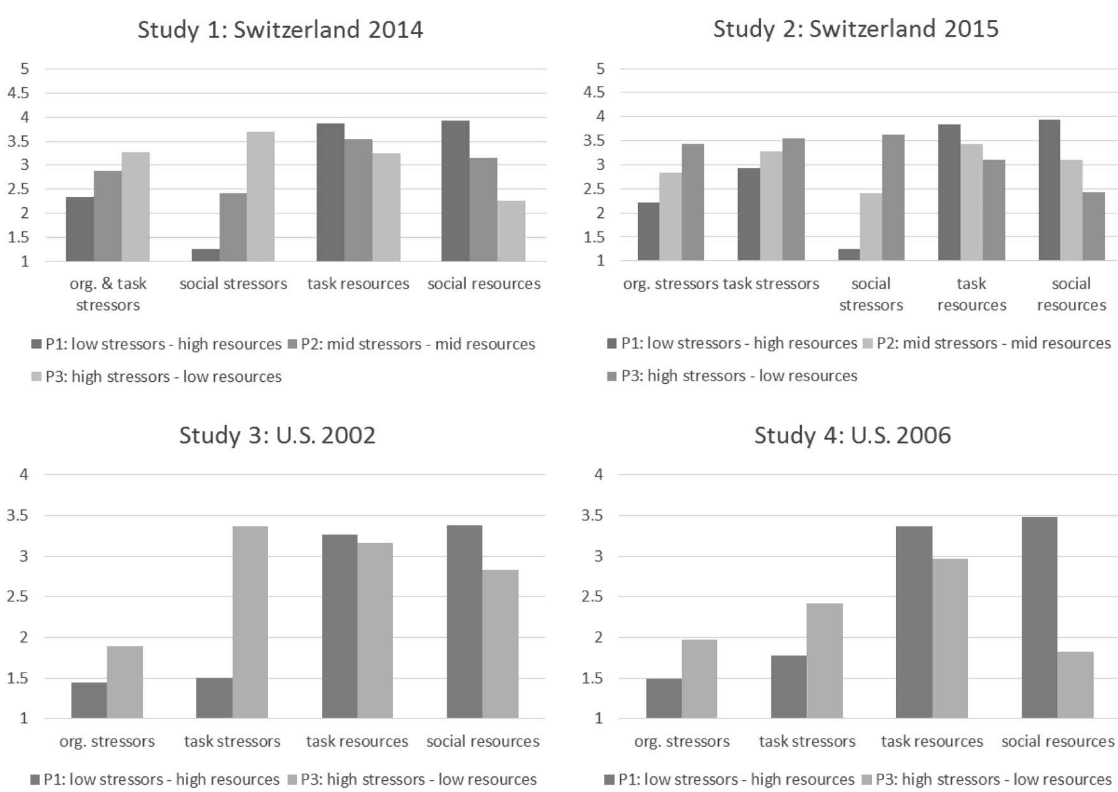

Figure 1. Mean values of factors sorted by profiles across the four studies.

Overall, these results regarding Research Question 1 indicate that meaningfully different constellations of job stressors and job resources exist. Notably, we did not identify all four of the profiles proposed by Karasek (1979). Although we found profiles consistent with high-strain jobs and low-strain jobs, we found no profiles that resembled active jobs or passive jobs.

Validation of Profiles: Differences in Outcomes

We compared the profiles in terms of their relationships with job satisfaction, exhaustion, general health, and performance. As noted above, subjective performance was only available for the Swiss samples (Studies 1 and 2). In all four studies, the identified profiles explained considerable variance in job satisfaction (partial-eta^2 effect sizes ranged from .04 to .19 across the four studies) and exhaustion (effect sizes ranged from .03 to .10). Profiles were less strongly related to general health and performance (effect sizes ranged from .01 to .03).

Table 4 shows mean values of outcome variables across the profiles. Across all four studies, the profiles differed significantly with respect to the outcome variables. Employees in profiles with lower levels of job stressors and higher levels of resources (P1: low stressors—high resources) reported higher levels of job satisfaction, general health, and performance, and lower levels of exhaustion (see Table 4). By contrast, employees in profiles with higher job stressors and lower job resources reported less favorable mean levels of outcome variables. Specifically, employees in profile P2 (mid stressors—mid resources) reported somewhat lower levels of well-being and behavioral outcomes than P1, but significantly higher levels than P3 (high stressors—low resources). These results shed light on our Research Question 2, demonstrating that the profiles seem to meaningfully differentiate outcomes, and these differences seem to be associated with overall levels of stressors and resources.

Additional Analyses

In addition, we assessed whether profiles remained significant predictors of outcome variables after employees' scale scores on job stressors, resources, and the interaction of stressors and resources were included in the equations. The class variable remained significant in predicting exhaustion (see Table 5), but not job satisfaction (results for job satisfaction included in supplemental material). Table 5 shows standardized regression coefficients predicting exhaustion in the three steps. Apparently due to multicollinearity, classes switched from being positive predictors to being negative predictors of exhaustion in Studies 1 and 2 (for an interpretation of these results see the Discussion).

Tables 6 and 7 show the results for the two regression analyses performed to assess the relationship between job attribute factors and outcomes within each profile. Across all four studies, for employees in the constellation of generally low job stressors and high job resources (P1), almost all job factors seemed relevant for employees' job satisfaction. In comparison, among employees who perceived their job as characterized by high job stressors and low resources (P3), social resources were more strongly associated with job satisfaction. In contrast to P1, members of P3 did not report clear relationships between job attributes and job satisfaction other than with social resources. Among employees in P1 (low stressors—high resources), there was a consistently positive relationship between task-related stressors and exhaustion across all four studies (see Table 7). Among employees in P3 (high stressors—low resources), no consistent pattern emerged; however, three out of four regression coefficients were significantly related to task-related stressors and two to task resources. These results indicate that different aspects of one's work are relevant, depending on the overall constellation. Also these associations differed depending on the outcome.

Discussion

We sought to identify empirical constellations of job stressors and job resources among four large samples of employees and to validate these by examining their correspondence with employee well-being and behavior. We applied factor mixture modeling to extract the profiles. Overall, our results showed that there was heterogeneity in job stressors and resources within populations of employees, which could be captured by two to three different

Table 4
Mean Levels and Differences Across the Profiles in Terms of Outcomes

Outcome	P1	P2	P3
Job satisfaction S1	5.54 (.24)$_{P2,P3}$	4.73 (−.43)$_{P1,P3}$	3.74 (−1.26)$_{P1,P2}$
Job satisfaction S2	5.63 (.21)$_{P2,P3}$	4.95 (−.40)$_{P1,P3}$	4.19 (−1.08)$_{P1,P2}$
Job satisfaction S3	3.41 (.10)$_{P3}$	—	3.00 (−.43)$_{P1}$
Job satisfaction S4	3.36 (.11)$_{P3}$	—	2.72 (−.76)$_{P1}$
Exhaustion S1	1.99 (−.18)$_{P2,P3}$	2.28 (.36)$_{P1,P3}$	2.53 (.82)$_{P1,P2}$
Exhaustion S2	1.97 (−.16)$_{P2,P3}$	2.25 (.35)$_{P1,P3}$	2.44 (.70)$_{P1,P2}$
Exhaustion S3	3.22 (−.12)$_{P3}$	—	3.94 (.53)$_{P1}$
Exhaustion S4	3.32 (−.06)$_{P3}$	—	3.87 (.42)$_{P1}$
General health S1	4.12 (.09)$_{P2,P3}$	3.95 (−.17)$_{P1,P3}$	3.73 (−.45)$_{P1,P2}$
General health S2	4.14 (.08)$_{P2,P3}$	3.95 (−.19)$_{P1}$	3.83 (−.36)$_{P1}$
General health S3	3.75 (.03)$_{P3}$	—	3.57 (−.15)$_{P1}$
General health S4	3.71 (.04)$_{P3}$	—	3.37 (−.29)$_{P1}$
Performance S1	8.20 (.07)$_{P2,P3}$	7.97 (−.11)$_{P1,P3}$	7.61 (−.39)$_{P1,P2}$
Performance S2	8.10 (.06)$_{P2,P3}$	7.90 (−.11)$_{P1}$	7.68 (−.28)$_{P1}$

Note. Sx = Study x; P1: low stressors—high resources; P2: mid stressors—mid resources; P3: high stressors—low resources. Means were controlled for gender, age, holding a part-time job, and private stressors. Z-values are given in parentheses. Subscripts indicate that profiles were significantly different at $p < .01$.

Table 5
Standardized Regression Coefficients and Explained Variance of Classes and Job Attributes for Exhaustion

	Study 1 (N = 3,028)				Study 2 (N = 2,535)				Study 3 (N = 1,390)				Study 4 (N = 1,299)			
	1	2	3		1	2	3		1	2	3		1	2	3	
Step	β	β	β	r	β	β	β	r	β	β	β	r	β	β	β	r
Class(es)	.25*** .28***	−.08*** −.13***	−.09*** −.14***	.21 .24	.21*** .26***	−.07*** −.13***	−.07*** −.10***	.18 .23	.27***	.11**	.11**	.27	.17***	.09**	.10**	.17
Stressors		.53***	.53***	.52		.48***	.49***	.53		.24***	.24***	.33		.27***	.28***	.30
Resources		−.17***	−.17***	−.40		−.23***	−.23***	−.44		−.03	−.03	−.17		.03	.03	−.14
Interaction s × r			−.02	−.20			.05*	−.13			.01	−.11			.02	−.08
R^2	.12	.30	.30		.10	.31	.31		.07	.11	.11		.03	.09	.09	
ΔR^2		.18***	<.01			.22***	<.01			.04***	<.01			.06***	<.01	

Note. Step 1: classes; Step 2: stressors and resources (centered); Step 3: interaction stressors × resources. Coding of classes: in Study 1 and 2, classes were represented by two dummy variables (P1: low stressors—high resources represented the reference group, first coefficient P2: mid stressors—mid resources, and second coefficient P3: high stressors—low resources). In Study 3 and 4, one dummy variable was used (P3: high stressors—low resources coded as 1). R^2 = explained variance; ΔR^2 = change in explained variance.
* $p < .05$. ** $p < .01$. *** $p < .001$.

profiles. In all four studies, we found a profile that was mostly characterized by low stressors and high resources (P1) and a profile that showed the reversed pattern of relatively high stressors and low resources (P3). For the Swiss population, a third profile was extracted that was characterized by stressors and resources that were near to the midpoint of the sample (P2). Empirical evidence for a third profile was not sufficient in the U.S. samples (see Table 2). Therefore, we will focus our discussion on the two replicable profiles we found in all four samples.

We were not able to identify two out of the four profiles specified by Karasek (1979). Specifically, our data yielded no profile characterized by high stressors and high resources (i.e., “active job”), and no profile characterized by low stressors and low resources (i.e., “passive job”). This finding suggests that what is a theoretical possibility does not necessarily reflect employees’ experiences at work. The results are particularly cautionary about using preestablished or arbitrary cut-off points in the distribution of variables (e.g., median splits) to categorize employees.

Across the four studies, the extracted profiles differed mainly in terms of the levels of organizational stressors and social aspects of work. The profiles in our studies did not differ substantially in terms of job attributes, as previous research had suggested (Holman, 2013). In contrast to task-related attributes, employees may feel that they have less control over organizational stressors and social stressors at work. This would make organizational and social stressors most important for the overall constellation. In three out of the four studies, social aspects at work differed substantially between the profiles. In Study 3 (U.S.-2002), however, the mean level difference was not as large as found in the other three studies. These results may reflect a shift in the rele-

Table 6
Standardized Regression Coefficients for Relationship Between Job Attribute Factors and Job Satisfaction Across the Profiles

	Org. stressors	Task-related stressors	Social stressors	Task resources	Social resources	$R^2/\Delta R^2$
S1 all P	−.19***		−.13***	.13***	.37***	.42/.41***
S2 all P	−.15***	−.06**	−.05*	.11***	.38***	.36/.33***
S3 all P	−.17***	−.05 (ns)	na	.27***	.30***	.38/.34***
S4 all P	−.13***	−.03 (ns)	na	.30***	.30***	.33/.32***
S1 P1	−.23***		−.10***	.14***	.29***	.28/.27***
S2 P1	−.15**	−.09***	−.04	.09***	.32***	.26/.23***
S3 P1	−.21***	−.01 (ns)	na	.27***	.26***	.34/.32***
S4 P1	−.14***	−.01 (ns)	na	.32***	.23***	.29/.27***
S1 P2	−.14***		−.04 (ns)	.15***	.38***	.26/.25***
S2 P2	−.11*	−.02 (ns)	.02 (ns)	.21***	.40***	.27/.26***
S1 P3	−.07 (ns)		−.14*	.09 (ns)	.49***	.33/.31***
S2 P3	−.20**	−.10 (ns)	.03 (ns)	.09 (ns)	.28***	.24/.19***
S3 P3	−.03 (ns)	−.04 (ns)	na	.32***	.32***	.43/.30***
S4 P3	−.10 (ns)	−.11 (ns)	na	.28***	.27***	.27/.24***

Note. Sx = Study x; all P = whole sample; P1: low stressors—high resources; P2: mid stressors—mid resources; P3: high stressors—low resources. In the first study, a four-factor solution fitted best to the data (combination of organizational and task stressors). na = not available. Models were controlled for gender, age, part-time, and private stressors. R^2 = explained variance; ΔR^2 = amount of additional explained variance through job attribute factors.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 7
Standardized Regression Coefficients for Relationship Between Job Attribute Factors and Exhaustion Across the Profiles

	Org. stressors	Task-related stressors	Social stressors	Task resources	Social resources	$R^2/\Delta R^2$
S1 all P	.35***		.11***	−.11***	−.10***	.34/.26***
S2 all P	.07*	.32***	.04 (ns)	−.14***	−.19***	.36/.28***
S3 all P	.02 (ns)	.28***	na	−.01 (ns)	−.06*	.17/.10***
S4 all P	.03 (ns)	.23***	na	.03 (ns)	−.11***	.13/.09***
S1 P1	.35***		.06**	−.11***	−.06**	.25/.18***
S2 P1	.09***	.34***	.08***	−.14***	−.14***	.33/.25***
S3 P1	.04 (ns)	.20***	na	.01 (ns)	−.04 (ns)	.12/.05***
S4 P1	.03 (ns)	.24***	na	.03 (ns)	−.06 (ns)	.11/.08***
S1 P2	.30***		.13**	−.13**	−.12**	.27/.21***
S2 P2	.01 (ns)	.26***	.04 (ns)	−.14**	−.25***	.21/.17***
S1 P3	.28***		.12 (ns)	−.11 (ns)	−.20**	.24/.21***
S2 P3	−.01 (ns)	.31***	−.01 (ns)	−.19**	−.13 (ns)	.22/.17***
S3 P3	−.06 (ns)	.04 (ns)	na	−.15*	−.13 (ns)	.06/.05*
S4 P3	.04 (ns)	.16*	na	−.07 (ns)	−.04 (ns)	.16/.04 (ns)

Note. Sx = Study x; all P = whole sample; P1: low stressors—high resources; P2: mid stressors—mid resources; P3: high stressors—low resources. In the first study, a four-factor solution fitted best to the data (combination of organizational and task stressors). na = not available. Models were controlled for gender, age, part-time, and private stressors. R^2 = explained variance; ΔR^2 = amount of additional explained variance through job attribute factors.
* $p < .05$. ** $p < .01$. *** $p < .001$.

vance of certain job aspects over time, as Study 3 was conducted in 2002, whereas the data for the other studies were collected in 2006, 2014, and 2015. Scholars have suggested that developments in the labor market and generational shifts have made social aspects of work more important to employees now than is reflected in research conducted over a decade ago (e.g., Colbert, Bono, & Purvanova, 2015; Grant & Parker, 2009). In sum, our results imply that organizational stressors and social aspects of work make a substantial difference for employees.

The profiles were associated with outcome variables based on the JDC (Karasek, 1979) and JD-R (Demerouti et al., 2001) models as expected. Predictably, employees in the constellations with the highest job stressors and lowest resources reported the lowest mean levels of job satisfaction, subjective performance, and general health, and the highest mean level of exhaustion.

The profiles appeared to capture meaningful aspects of employees' work experience, although they differed somewhat across societal settings. Showing that profiles capture meaningful aspects of work is only one part of our results, however. The second part investigated if profiles yield more information than the traditional prediction of well-being. Our results are mixed in this regard. Profile membership did not predict job satisfaction beyond the prediction of job stressors and resources. For exhaustion, profile membership did explain additional variance, however, in the regression models for the Swiss studies there was a reversal of sign, apparently due to multicollinearity. This suggests an equivalence for the two approaches in the Swiss studies. Because in the U.S. samples the profiles explained additional variance in exhaustion but not in job satisfaction, the constellations may have more important implications for health processes than for employee morale. The picture regarding the possible value of our results for occupational health psychology changes, however, if we look at the prediction of well-being within classes, which we discuss next.

From previous research, we know that many job stressors are associated with well-being and behavior (e.g., for meta-analytical results see Humphrey et al., 2007). Our results contribute to our understanding by suggesting that there is a qualification to these associations depending on the overall constellation of job attributes. For example, among employees in one of the more favorable constellations (i.e., one that is not characterized by high levels of stressors and low levels of resources; P1 or P2), almost all factors were significantly associated with job satisfaction, but among employees in the less favorable constellation, only social resources were consistently associated with job satisfaction. Tables 6 and 7 show comparable standard deviations around mean job attributes across the profiles. Therefore, the differences between the profiles are not attributable to restrictions in the ranges of variables within a profile. An important implication for occupational health psychology may derive from this. In our study, the vast majority of employees were categorized in favorable profiles (P1 or P2). This may reflect the constellations of employees in many occupational health psychology studies. Results based on these heterogeneous samples may produce reliable and valid results of relevant predictors and their interactions for employees in relatively favorable constellations but generalization of these results to employees with less favorable constellations may not be warranted.

Beyond the continuous relationships between job stressors and resources and outcomes, our results showed that there are relevant thresholds that capture where a constellation becomes unfavorable for employees. Applying factor mixture modeling to job attributes, as we have done in this study, may thus be valuable for establishing cut-off scores for risk assessment (Lubke & Spies, 2008). Using FMM latent profile membership as a criterion, cut-off values can be derived by examining sensitivity and specificity. Sensitivity means that individuals are categorized into a group to which they truly belong, and specificity relates to not categorizing individuals into groups to which they do not belong. This procedure also yields a percentage of classification accuracy. Typically, risk assessment in occupational health contexts uses standard deviations around the mean of single job attributes. Because FMM-derived profiles account for the constellation of various attributes, the profiles may yield more precise classifications of at-risk groups (cf. Allan, Korte, Capron, Raines, & Schmidt, 2014; Allan, Raines et al., 2014).

Theoretical Implications

Theoretical models of job stress and employee health and well-being, most prominently the JDC and ERI, have been criticized for being too narrow and overly simplistic because they only focus on a few job attributes. These few attributes may not fully reflect employees' reality, leading some researchers to question whether these models can be generalized to the diverse jobs and positions in the labor market (e.g., Bakker & Demerouti, 2007; Parker, Wall, & Cordery, 2001). In addition, these models postulate that some job attributes are considerably more important than others (e.g., job control in JDC). The JD-R model extends these theoretical models to include various job stressors and resources, and a range of job attributes (Bakker & Demerouti, 2007; Demerouti et al., 2001). Consequently, our results are more consistent with the JD-R than with other perspectives.

The profiles we identified differed mainly in their overall mean levels of job stressors and resources; none of the profiles were characterized by extreme means for particular attributes. In effect, the job stressors and job resources were, *in combination*, either relatively favorable or relatively unfavorable. Furthermore, there was no crossover, in that neither of the favorable profiles (P1 and P2) had higher levels of stressors than the third profile (P3). Employees with many resources also reported fewer stressors, and a higher level of one type of stressor was associated with higher levels of other stressors. This finding might be interpreted in light of resource gain spirals as suggested by conservation of resources theory (Hobfoll, 1989). Certain job stressors may initially affect well-being and health (e.g., high workload may heighten depression). Impaired well-being and health may then amplify stressors and reduce perceived resources (e.g., depression has negative effects on organizational justice perceptions over time; Lang, Bliese, Lang, & Adler, 2011). Such mechanisms may lead to a drift toward poor job qualities for some employees over time.

Although some employees may experience a very high level of a certain stressor, our results seem to support the idea that accumulation of stressors and lack of resources is more critical to well-being. Such an accumulation is often conceptualized over time (Zapf, Dormann, & Frese, 1996); however, there is also the possibility that, at a given moment in time, there are just too many job stressors and too few job resources for an employee to cope with them, which leads to a general experience of high stressors and limited resources. Employees may be prone to specific emotional reactions when exposed to certain job attributes (e.g., anger when confronted with an unsupportive supervisor), while the whole combination of attributes may also either deplete or help to restore an employee's energy. The extent of energy depletion or opportunities for recovery could be an indicator of how employees differentiate between good and poor quality jobs. In pursuing the possible implications of loss spirals and accumulation, future research may investigate if, how, and under what circumstances employees recover from exposure to a constellation characterized by high stressors and low resources.

Limitations and Future Research Directions

The study data were limited to self-reports, which could raise concerns about common method variance. However, the primary focus of the study was on extraction of profiles. The factor mixture modeling method clusters employees rather than observations. Although the relationships between the levels of variables that spanned the profiles could be influenced by common method variance, it is less likely that the distinctly different combinations of the levels of these variables across the profiles were the result of the common source of measurement. The role of common method variance in the relationships between profiles and outcome variables would be of greater concern, yet these analyses served only as a means to validate the profiles. Importantly, we found that relationships between job stressors and resources and outcomes were moderated by profile membership. Researchers have found that method bias cannot produce spurious interaction effects (Evans, 1985; Siemsen, Roth, & Oliveira, 2010). It is therefore unlikely that the core validation findings could be attributed to common method variance. Nevertheless, we would encourage researchers to further validate our results using, for example, multiple sources.

We were able to investigate a number of job characteristics in terms of stressors and resources related to organizational, task-related, and social aspects. Not reported here are profiles including job insecurity. Because this characteristic was only available for two studies (Studies 2 and 4), we did not include it in reporting our primary results. However, supplemental analyses showed that job insecurity loaded on the factor of organizational stressors. Studies 2 and 4 yielded the same number of profiles irrespective of whether job insecurity was included, and the association between profiles and outcomes remained the same. These findings demonstrate the robustness of the obtained classes.

Nevertheless, there are job attributes that were not included in our studies. Future research may investigate the extent to which other job attributes (e.g., occupation-specific attributes or job attributes such as those highlighted by Hackman & Oldham, 1976) refine classes or simply add another factor to the favorable and unfavorable profiles respectively. Future research may also place a greater emphasis on motivational outcome indicators, which were underrepresented in the studies reported here.

Previous research has shown that high levels of job stressors increase the likelihood of study nonresponse (Barr, Spitzmuller, & Stuebing, 2008). This could have affected the number of profiles we extracted. Future research may aim to overcome this limitation by specifically recruiting employees who experience high levels of job stressors.

The application of factor mixture modeling in the occupational health context shows a new way to identify at-risk groups based on various job attributes. Future research may investigate the extent to which members of these profiles differ, for example, in terms of abilities and skills. These profiles can also be used to investigate the possibility of differential effects of interventions. In addition, longitudinal research may investigate stability of profile membership and development of well-being as a function of profile membership. Furthermore, identifying subgroups may also aid future research investigating job stressors and resources that may not be relevant for all employees or are less broad in nature. For example, research on discrimination in the workplace showed that the strength of the effect of discrimination depended, among other factors, on the extent of the representation of one's ethnic group in the organization (Sanchez & Brock, 1996). In order to investigate these effects, Sanchez and Brock (1996) had to limit their sample to a group they assumed would be exposed to and affected by discrimination. By relying solely on top-down approaches to occupational health research, we may underestimate the relevance of some stressors and how harmful they are to specific subgroups of employees. Using factor mixture modeling and the profiles derived may enable occupational health research to identify these subgroups and the job stressors most harmful to them.

Conclusion

This study demonstrated how factor mixture modeling can be usefully applied in research on occupational health psychology. The results demonstrate that linear effects of job stressors and resources are important, but overall constellations deserve attention as well. Organizational stressors and social aspects were the factors that most clearly differentiated factors between the profiles. Managers and supervisors can influence social aspects relatively easily through training. The results also show that employees experiencing stressful combinations of job attributes may benefit from work redesign targeted at social resources and task-related aspects but not at other job attributes.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transaction on Automatic Control, 19,* 716–723.

Allan, N. P., Korte, K. J., Capron, D. W., Raines, A. M., & Schmidt, N. B. (2014). Factor mixture modeling of anxiety sensitivity: A three-class structure. *Psychological Assessment, 26,* 1184–1195. http://dx.doi.org/10.1037/a0037436

Allan, N. P., Raines, A. M., Capron, D. W., Norr, A. M., Zvolensky, M. J., & Schmidt, N. B. (2014). Identification of anxiety sensitivity classes and clinical cut-scores in a sample of adult smokers: Results from a factor mixture model. *Journal of Anxiety Disorders, 28,* 696–703. http://dx.doi.org/10.1016/j.janxdis.2014.07.006

Arminger, G., Stein, P., & Wittenberg, J. (1999). Mixtures of conditional mean- and covariance-structure models. *Psychometrika, 64,* 475–494. http://dx.doi.org/10.1007/BF02294568

Bagozzi, R. P., & Edwards, J. R. (1998). A general approach to representing constructs in organizational research. *Organizational Research Methods, 1,* 45–87. http://dx.doi.org/10.1177/109442819800100104

Baillod, J., & Semmer, N. K. (1994). Fluktuation und Berufsverläufe bei Computerfachleuten [Turnover and career paths of computer specialists]. *Zeitschrift für Arbeits- und Organisationspsychologie, 38,* 152–163.

Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of Managerial Psychology, 22,* 309–328. http://dx.doi.org/10.1108/02683940710733115

Bakker, A. B., Hakanen, J. J., Demerouti, E., & Xanthopoulou, D. (2007). Job resources boost work engagement, particularly when demands are high. *Journal of Educational Psychology, 99,* 274–284. http://dx.doi.org/10.1037/0022-0663.99.2.274

Barr, C. D., Spitzmüller, C., & Stuebing, K. K. (2008). Too stressed out to participate? Examining the relation between stressors and survey response behavior. *Journal of Occupational Health Psychology, 13,* 232–243. http://dx.doi.org/10.1037/1076-8998.13.3.232

Bauer, D. J., & Curran, P. J. (2004). The integration of continuous and discrete latent variable models: Potential problems and promising opportunities. *Psychological Methods, 9,* 3–29. http://dx.doi.org/10.1037/1082-989X.9.1.3

Bosma, H., Marmot, M. G., Hemingway, H., Nicholson, A. C., Brunner, E., & Stansfeld, S. A. (1997). Low job control and risk of coronary heart disease in Whitehall II (prospective cohort) study. *British Medical Journal, 314,* 558–565. http://dx.doi.org/10.1136/bmj.314.7080.558

Bowling, N. A., & Beehr, T. A. (2006). Workplace harassment from the victim's perspective: A theoretical model and meta-analysis. *Journal of Applied Psychology, 91,* 998–1012. http://dx.doi.org/10.1037/0021-9010.91.5.998

Clark, S. L., Muthén, B., Kaprio, J., D'Onofrio, B. M., Viken, R., & Rose, R. J. (2013). Models and strategies for factor mixture analysis: An example concerning the structure underlying psychological disorders. *Structural Equation Modeling, 20,* 681–703. http://dx.doi.org/10.1080/10705511.2013.824786

Colbert, A., Bono, J., & Purvanova, R. (2015). Flourishing via workplace relationships: Moving beyond instrumental support. *Academy of Management Journal*. Advance online publication. http://dx.doi.org/10.5465/amj.2014.0506

Dawis, R. V., & Lofquist, L. H. (1984). *A psychological theory of work adjustment*. Minneapolis, MN: University of Minnesota Press.

De Lange, A. H., Taris, T. W., Kompier, M. A. J., Houtman, I. L. D., & Bongers, P. M. (2004). The relationships between work characteristics and mental health: Examining normal, reversed and reciprocal relationships in a 4-wave study. *Work and Stress, 18,* 149–166. http://dx.doi.org/10.1080/02678370412331270860

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology, 86,* 499–512. http://dx.doi.org/10.1037/0021-9010.86.3.499

Dormann, C., & Zapf, D. (2004). Customer-related social stressors and burnout. *Journal of Occupational Health Psychology, 9,* 61–82. http://dx.doi.org/10.1037/1076-8998.9.1.61

Elovainio, M., Ferrie, J. E., Singh-Manoux, A., Gimeno, D., De Vogli, R., Shipley, M. J., . . . Kivimäki, M. (2009). Cumulative exposure to high-strain and active jobs as predictors of cognitive function: The Whitehall II study. *Occupational and Environmental Medicine, 66,* 32–37. http://dx.doi.org/10.1136/oem.2008.039305

Evans, M. G. (1985). A Monte Carlo study of the effects of correlated method variance in moderated multiple regression analysis. *Organizational Behavior and Human Decision Processes, 36,* 305–323. http://dx.doi.org/10.1016/0749-5978(85)90002-0

Findlay, P., Kalleberg, A. L., & Warhurst, C. (2013). The challenge of job quality. *Human Relations, 66,* 441–451. http://dx.doi.org/10.1177/0018726713481070

French, J. R., Caplan, R. D., & Van Harrison, R. (1982). *The mechanisms of job stress and strain*. New York, NY: Wiley.

Frese, M., & Zapf, D. (1987). Eine Skala zur Erfassung von sozialen Stressoren am Arbeitsplatz [A scale to assess social stressors in the workplace]. *Zeitschrift fur Arbeitswissenschaft, 3,* 134–141.

Gabriel, A. S., Daniels, M. A., Diefendorff, J. M., & Greguras, G. J. (2015). Emotional labor actors: A latent profile analysis of emotional labor strategies. *Journal of Applied Psychology, 100,* 863–879. http://dx.doi.org/10.1037/a0037408

Geurts, S. A., Taris, T. W., Kompier, M. A., Dikkers, J. S., Van Hooff, M. L., & Kinnunen, U. M. (2005). Work-home interaction from a work psychological perspective: Development and validation of a new questionnaire, the SWING. *Work and Stress, 19,* 319–339. http://dx.doi.org/10.1080/02678370500410208

Gilboa, S., Shirom, A., Fried, Y., & Cooper, C. (2008). A meta-analysis of work demand stressors and job performance: Examining main and moderating effects. *Personnel Psychology, 61,* 227–271. http://dx.doi.org/10.1111/j.1744-6570.2008.00113.x

Goldstone, R. L. (1994). The role of similarity in categorization: Providing a groundwork. *Cognition, 52,* 125–157. http://dx.doi.org/10.1016/0010-0277(94)90065-5

Grant, A. M., & Parker, S. K. (2009). Redesigning work design theories: The rise of relational and proactive perspectives. *The Academy of Management Annals, 3,* 317–375. http://dx.doi.org/10.1080/19416520903047327

Greenbaum, P. E., Del Boca, F. K., Darkes, J., Wang, C.-P., & Goldman, M. S. (2005). Variation in the drinking trajectories of freshmen college students. *Journal of Consulting and Clinical Psychology, 73,* 229–238. http://dx.doi.org/10.1037/0022-006X.73.2.229

Guest, D. E., Oakley, P., Clinton, M., & Budjanovcanin, A. (2006). Free or precarious? A comparison of the attitudes of workers in flexible and traditional employment contracts. *Human Resource Management Review, 16,* 107–124. http://dx.doi.org/10.1016/j.hrmr.2006.03.005

Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational Behavior and Human Performance, 16,* 250–279. http://dx.doi.org/10.1016/0030-5073(76)90016-7

Häusser, J. A., Mojzisch, A., Niesel, M., & Schulz-Hardt, S. (2010). Ten years on: A review of recent research on the job demand–control (–support) model and psychological well-being. *Work and Stress, 24,* 1–35. http://dx.doi.org/10.1080/02678371003683747

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

Holman, D. (2013). Job types and job quality in Europe. *Human Relations, 66,* 475–502. http://dx.doi.org/10.1177/0018726712456407

Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: A meta-analytic summary and theoretical extension of the work design literature. *Journal of Applied Psychology, 92,* 1332–1356. http://dx.doi.org/10.1037/0021-9010.92.5.1332

Ilies, R., Dimotakis, N., & De Pater, I. E. (2010). Psychological and physiological reactions to high workloads: Implications for well-being. *Personnel Psychology, 63,* 407–436. http://dx.doi.org/10.1111/j.1744-6570.2010.01175.x

Jedidi, K., Jagpal, H. S., & DeSarbo, W. S. (1997). Finite-mixture structural equation models for response-based segmentation and unobserved heterogeneity. *Marketing Science, 16,* 39–59. http://www.jstor.org/stable/184129

Jedidi, K., Ramaswamy, V., & DeSarbo, W. S. (1993). A maximum likelihood method for latent class regression involving a censored dependent variable. *Psychometrika, 58,* 375–394. http://dx.doi.org/10.1007/BF02294647

Jex, S. M. (1998). *Stress and job performance: Theory, research, and implications for managerial practice*. Thousand Oaks, CA: Sage.

Karasek, R. A. (1979). Job demands, job decision latitude, and mental strain: Implications for job redesign. *Administrative Science Quarterly, 24,* 285–308. http://www.jstor.org/stable/2392498

Karasek, R. A., & Theorell, T. (1990). *Healthy work: Stress, productivity, and the reconstruction of working life*. New York, NY: Basic Books.

Karasek, R. A., Triantis, K. P., & Chaudhry, S. S. (1982). Co-worker and supervisor support as moderators of associations between task characteristics and mental strain. *Journal of Occupational Behaviour, 3,* 181–200. http://dx.doi.org/10.1002/job.4030030205

Kessler, R. C., Barber, C., Beck, A., Berglund, P., Cleary, P. D., McKenas, D., . . . Wang, P. (2003). The world health organization health and work performance questionnaire (HPQ). *Journal of Occupational and Environmental Medicine, 45,* 156–174. http://dx.doi.org/10.1097/01.jom.0000052967.43131.51

Kunin, T. (1955). The construction of a new type of attitude measure. *Personnel Psychology, 8,* 65–77. http://dx.doi.org/10.1111/j.1744-6570.1955.tb01189.x

Lang, J., Bliese, P. D., Lang, J. W., & Adler, A. B. (2011). Work gets unfair for the depressed: Cross-lagged relations between organizational justice perceptions and depressive symptoms. *Journal of Applied Psychology, 96,* 602–618. http://dx.doi.org/10.1037/a0022463

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika, 88,* 767–778. http://dx.doi.org/10.1093/biomet/88.3.767

Lubke, G. H., & Muthén, B. (2005). Investigating population heterogeneity with factor mixture models. *Psychological Methods, 10,* 21–39. http://dx.doi.org/10.1037/1082-989X.10.1.21

Lubke, G. H., & Spies, J. R. (2008). Choosing a "correct" factor mixture model: Power, limitations, and graphical data exploration. In G. R. Hancock & K. M. Samuelson (Eds.), *Advances in latent variable mixture models* (pp. 343–361). Charlotte, NC: Information Age Publishing.

McClelland, G. H., & Judd, C. M. (1993). Statistical difficulties of detecting interactions and moderator effects. *Psychological Bulletin, 114,* 376–390. http://dx.doi.org/10.1037/0033-2909.114.2.376

McLachlan, G., & Peel, D. (2004). *Finite mixture models*. New York, NY: Wiley.

Meijman, T. F., & Mulder, G. (1998). Psychological aspects of workload. In P. J. D. Drenth, H. Thierry, & C. J. de Wolff (Eds.), *Work psychology* (pp. 5–33). East Sussex, UK: Psychology Press.

Meredith, W. (1993). Measurement invariance, factor analysis and factorial invariance. *Psychometrika, 58,* 525–543. http://dx.doi.org/10.1007/BF02294825

Mervis, C. B., & Rosch, E. (1981). Categorization of natural objects. *Annual Review of Psychology, 32,* 89–115. http://dx.doi.org/10.1146/annurev.ps.32.020181.000513

Meyer, J. P., Stanley, L. J., & Vandenberg, R. J. (2013). A person-centered approach to the study of commitment. *Human Resource Management Review, 23,* 190–202. http://dx.doi.org/10.1016/j.hrmr.2012.07.007

Muthén, B. (2001). *Latent variable mixture modeling*. Mahwah, NJ: Erlbaum.

Muthén, L. K., & Muthén, B. O. (1998–2012). *Mplus user's guide* (7th ed.). Los Angeles, CA: Author.

Ng, T. W. H., & Feldman, D. C. (2008). Long work hours: A social identity perspective on meta-analysis data. *Journal of Organizational Behavior, 29,* 853–880.

Ng, T. W. H., & Feldman, D. C. (2014). Embeddedness and well-being in the United States and Singapore: The mediating effects of work-to-family and family-to-work conflict. *Journal of Occupational Health Psychology, 19,* 360–375. http://dx.doi.org/10.1037/a0036922

Parker, S. K., Wall, T. D., & Cordery, J. L. (2001). Future work design research and practice: Towards an elaborated model of work design. *Journal of Occupational and Organizational Psychology, 74,* 413–440. http://dx.doi.org/10.1348/096317901167460

Peters, L. H., O'Connor, E. J., Eulberg, J. R., & Watson, T. W. (1988). An examination of situational constraints in Air Force work settings. *Human Performance, 1,* 133–144. http://dx.doi.org/10.1207/s15327043hup0102_4

Pindek, S., & Spector, P. E. (2016). Organizational constraints: A meta-analysis of a major stressor. *Work and Stress, 30,* 7–25. http://dx.doi.org/10.1080/02678373.2015.1137376

Porac, J. F., & Thomas, H. (1994). Cognitive categorization and subjective rivalry among retailers in a small city. *Journal of Applied Psychology, 79,* 54–66. http://dx.doi.org/10.1037/0021-9010.79.1.54

Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology, 7,* 573–605. http://dx.doi.org/10.1016/0010-0285(75)90024-9

Sanchez, J. I., & Brock, P. (1996). Outcomes of perceived discrimination among Hispanic employees: Is diversity management a luxury or a necessity? *Academy of Management Journal, 39,* 704–719. http://dx.doi.org/10.2307/256660

Schaubroeck, J., & Ganster, D. C. (1993). Chronic demands and responsivity to challenge. *Journal of Applied Psychology, 78,* 73–85. http://dx.doi.org/10.1037/0021-9010.78.1.73

Schaufeli, W. B., & Bakker, A. B. (2004). Job demands, job resources, and their relationship with burnout and engagement: A multi-sample study. *Journal of Organizational Behavior, 25,* 293–315. http://dx.doi.org/10.1002/job.248

Schaufeli, W. B., Bakker, A. B., & Van Rhenen, W. (2009). How changes in job demands and resources predict burnout, work engagement, and sickness absenteeism. *Journal of Organizational Behavior, 30,* 893–917. http://dx.doi.org/10.1002/job.595

Schnall, P. L., Schwartz, J. E., Landsbergis, P. A., Warren, K., & Pickering, T. G. (1998). A longitudinal study of job strain and ambulatory blood pressure: Results from a three-year follow-up. *Psychosomatic Medicine, 60,* 697–706. http://dx.doi.org/10.1097/00006842-199811000-00007

Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics, 6,* 461–464. http://dx.doi.org/10.1214/aos/1176344136

Semmer, N. K. (2006). Job stress interventions and the organization of work. *Scandinavian Journal of Work, Environment & Health, 32,* 515–527. http://dx.doi.org/10.5271/sjweh.1056

Semmer, N. K., Jacobshagen, N., Meier, L. L., & Elfering, A. (2007). Occupational stress research: The "stress-as-offense-to-self" perspective. In J. Houdmont & S. McIntyre (Eds.), *Occupational health psychology: European perspectives on research, education and practice* (Vol. 2, pp. 43–60). Castelo da Maia, Portugal: ISMAI Publishing.

Semmer, N. K., Zapf, D., & Dunckel, H. (1995). Assessing stress at work: A framework and an instrument. In O. Svane & C. Johansen (Eds.), *Work and health: Scientific basis of progress in the working environment*. Luxembourg, Belgium: Office for Official Publications of the European Communities.

Shieh, G. (2009). Detection of interactions between a dichotomous moderator and a continuous predictor in moderated multiple regression with heterogeneous error variance. *Behavior Research Methods, 41,* 61–74. http://dx.doi.org/10.3758/BRM.41.1.61

Siegrist, J. (1996). Adverse health effects of high-effort/low-reward conditions. *Journal of Occupational Health Psychology, 1,* 27–41. http://dx.doi.org/10.1037/1076-8998.1.1.27

Siemsen, E., Roth, A., & Oliveira, P. (2010). Common method bias in regression models with linear, quadratic, and interaction effects. *Organizational Research Methods, 13,* 456–476. http://dx.doi.org/10.1177/1094428109351241

Sonnentag, S., & Frese, M. (2012). Stress in organizations. In N. W. Schmitt & S. Highhouse (Eds.), *Handbook of psychology: Vol. 12. Industrial and organizational psychology* (2nd ed., pp. 560–592). Hoboken, NJ: Wiley.

Spector, P. E., & Bruk-Lee, V. (2008). Conflict, health, and well-being. In C. K. W. De Dreu & M. J. Gelfand (Eds.), *The psychology of conflict and conflict management in organizations* (pp. 267–288). San Francisco, CA: Jossey-Bass.

Stocker, D., Jacobshagen, N., Krings, R., Pfister, I. B., & Semmer, N. K. (2014). Appreciative leadership and employee well-being in everyday working life. *German Journal of Research in Human Resource Management, 28,* 73–95.

Tsai, S. S., Lai, C. H., Shih, T. S., Lin, M. H., & Liou, S. H. (2014). High job strain is associated with inflammatory markers of disease in young long-haul bus drivers. *Journal of Occupational Health Psychology, 19,* 336–347. http://dx.doi.org/10.1037/a0036600

Udris, I., & Rimann, M. (1999). SAA und SALSA: Zwei Fragebozegen zur subjektiven Arbeitsanalyse [SAA and SALSA: 2 questionnaires for subjective job analysis]. In H. Dunckel (Ed.), *Handbuch psychologischer Arbeitsanalyseverfahren*. Ein praxisorientierter Überblick (pp. 397–419). Zurich, Switzerland: Vdf Hochschulverlag.

Viswesvaran, C., Sanchez, J., & Fisher, J. (1999). The role of social support in the process of work stress: A meta-analysis. *Journal of Vocational Behavior, 54,* 314–334. http://dx.doi.org/10.1006/jvbe.1998.1661

Xanthopoulou, D., Bakker, A. B., & Demerouti, E. (2007). The role of personal resources in the job demands-resources model. *International Journal of Health Management, 14,* 121–141.

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2009). Reciprocal relationships between job resources, personal resources, and work engagement. *Journal of Vocational Behavior, 74,* 235–244. http://dx.doi.org/10.1016/j.jvb.2008.11.003

Zapf, D., Dormann, C., & Frese, M. (1996). Longitudinal studies in organizational stress research: A review of the literature with reference to methodological issues. *Journal of Occupational Health Psychology, 1,* 145–169. http://dx.doi.org/10.1037/1076-8998.1.2.145

Received June 16, 2015
Revision received March 18, 2016
Accepted March 21, 2016 ■