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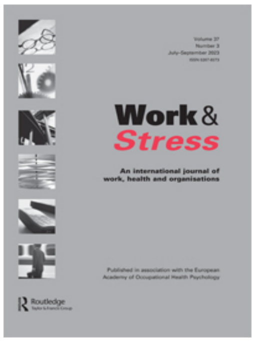

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REVIEW ARTICLE

Are all challenge stressors beneficial for learning? A meta-analytical assessment of differential effects of workload and cognitive demands

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ABSTRACT
Previous meta-analyses showed that challenge stressors are, though stressful, also motivating. However, their hypothesised gains related to learning are less well understood. In addition to the lack of meta-analytical assessments, there are conflicting theoretical perspectives on the learning effects of challenge stressors. In contrast to the challenge–hindrance stressor framework, action regulation theory posits that cognitive demands, but not workload, are conducive to learning. Furthermore, job control, the level of a stressor, and the type of occupation may moderate the effects of these two challenge stressors. Based on 417 independent samples collectively including 319,306 individuals, this meta-analysis tested the associations of workload and cognitive demands with learning, motivation, and strain and examined potential moderation effects. Results showed that workload was negatively related to learning and motivation and positively related to strain. Cognitive demands were positively related to learning and motivation and negatively related to strain. The detrimental effects of workload were more pronounced for care and social worker and for measures of overload. No moderations were found for country-level job control. Taken together, the results cast doubts on whether stressors can actually be simultaneously detrimental and beneficial, as neither workload nor cognitive demands were found to have such a pattern.

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Learning; work motivation; stress/strain; work/job characteristics; meta-analysis

Work stressors are varied and can include workload; role ambiguities; and cognitive, physical, and emotional demands. Various theoretical approaches have been developed to group stressors into broader categories that have similar effects on work-related outcomes. One such approach that has attracted considerable scientific attention in recent

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years (see, e.g. O'Brien & Beehr, 2019) is the challenge–hindrance stressor framework (Cavanaugh et al., 2000; Crawford et al., 2010; LePine et al., 2005). According to this framework, work stressors can be categorised as hindrance stressors (e.g. role ambiguity, red tape) or challenge stressors (e.g. workload, cognitive demands; Cavanaugh et al., 2000). Both hindrance stressors and challenge stressors draw on employees' physical and mental resources and can thus contribute to strain. However, a core tenet of the challenge–hindrance stressor framework is that, in addition to their adverse effects, challenge stressors (unlike hindrance stressors) are also associated with potential individual gains. These gains can be intrinsic rewards (e.g. motivation) but may also include work achievement or growth – for example, learning or skill development (Cavanaugh et al., 2000; LePine et al., 2005; O'Brien & Beehr, 2019).

While the negative effects of hindrance stressors on well-being, work engagement, motivation, and performance are well established (see Crawford et al., 2010; LePine et al., 2005; Mazzola & Disselhorst, 2019 for meta-analyses), the alleged positive effects of challenge stressors are less well understood and important questions remain to be answered. Among these is the role of challenge stressors for learning, a key workplace outcome (Parker, 2014), that remains controversial for several reasons. First, there are contradictory theoretical perspectives regarding the effects of specific challenge stressors on learning and the extent to which they help or hinder learning. The perspective of the challenge–hindrance stressor framework suggests that the most prominent challenge stressors, workload and cognitive demands are both conducive to learning (Cavanaugh et al., 2000; LePine et al., 2005). Yet, another perspective builds on action-regulation theory (Frese & Zapf, 1994; Zacher & Frese, 2018) which proposes that workload and cognitive demands differ in their effects on learning. According to action-regulation theory, workload is negatively related to learning because it restricts behavioural and (meta-)cognitive learning processes (Wielenga-Meijer et al., 2010). In contrast, cognitive demands stimulate such learning processes and may therefore be positively related to learning (Frese & Zapf, 1994; Glaser et al., 2015).

Second, although empirical evidence on the challenge–hindrance stressor framework has been summarised in various meta-analyses (Crawford et al., 2010; LePine et al., 2005), these have not included learning as a distinct outcome – in addition to motivation. This is a notable shortcoming considering that scholars have repeatedly highlighted the role of challenge stressors for learning and development (Brutus et al., 2000; Cavanaugh et al., 2000; Crawford et al., 2010; LePine et al., 2005). The goal of the present study is therefore to develop and test a theoretical account of the differential role of two key challenge stressors (i.e. workload and cognitive demands) for learning. Specifically, we will build on action-regulation theory (Frese & Zapf, 1994; Zacher & Frese, 2018) and propose that cognitive demands help while workload hinders learning. We will test these propositions with a meta-analysis that includes learning in addition to motivation and strain as outcomes and examines differential relationships across challenge stressors. In so doing, this work will contribute to the challenge–hindrance stressor framework by answering the question of which work stressors are motivating and conducive to learning and may therefore be considered challenges and which require alternate classification.

This is important because theoretical developments often build on the assumption that challenge stressors are beneficial for learning. For example, Crane and Searle (2016) theorise that exposure to challenge stressors could build resilience in employees because of the developmental opportunities that come with these stressors. The authors then test this hypothesis by combining workload and cognitive demands to operationalise challenge stressors and investigate their effects on resilience. If the effects of workload and cognitive demands on learning are in fact differential this could misguide the interpretation of results and hinder theoretical developments trying to build on the challenge–hindrance framework. In addition, classifying work stressors as beneficial for learning has also practical implications with regard to work design. Challenge stressors have been discussed as a potential pathway to design decent jobs that give employees opportunities to learn and develop (Parker, 2017; Parker et al., 2021). However, if work stressors which are considered challenge stressors, have no positive effect on learning, their incorrect classification will lead to wrong suggestions for work design.

Further, there is a longstanding and ongoing discussion on whether the effect of challenge stressors could be contingent on moderators (LePine et al., 2004; Mazzola & Disselhorst, 2019; O'Brien & Beehr, 2019). In particular, available resources (Bakker & Demerouti, 2014; Karasek & Theorell, 1990; O'Brien & Beehr, 2019; Parker, 2017), the severity of a challenge stressor (Edwards et al., 2014; O'Brien & Beehr, 2019; Parker, 2017), and the work context (Bakker & Sanz-Vergel, 2013; Searle & Auton, 2015) have often been discussed as potential moderating variables. Thus, to gain a deeper understanding of the generalizability of the beneficial effects of challenge stressors, this paper will meta-analytically test whether the amount of job control, the severity of workload (as reflected in its operationalisation as load or overload), or occupation moderates challenge stressors' relationships with learning, motivation, or strain.

This research will make three important contributions. First, it will contribute to the challenge–hindrance stressor framework by highlighting the role of learning as a discrete outcome of challenge stressors, in addition to motivation. In line with the work of Parker (2014, 2017), we propose learning, motivation, and strain to be proximal outcomes of work stressors that need to be considered in the challenge–hindrance stressor framework and that are likely responsible for mediating processes on more distal downstream outcomes, such as performance or organisational commitment (LePine et al., 2005; Podsakoff et al., 2007). By considering motivation and strain as outcomes alongside learning, the results can be compared with earlier meta-analyses, illuminating potential trade-offs among all three outcomes (Parker, 2017). Second, this study will refine the challenge–hindrance stressor framework by providing theoretical arguments based on action-regulation theory (Frese & Zapf, 1994; Zacher & Frese, 2018) for why and how workload and cognitive demands differentially relate to learning. To test these arguments, we will assess the relationships of workload and cognitive demands and their respective outcomes separately rather than by examining bundles of challenge stressors, as was customary in previous meta-analytical studies (LePine et al., 2005; Mazzola & Disselhorst, 2019). In this way, this work will advance scholarly knowledge on which work stressors can be classified as challenge stressors and which require an alternate classification. Third, this study will address the inconsistent findings in support of the motivating effect of workload by considering moderator variables. Consequently, this work will provide insights into whether and how much challenge stressors have general effects or depend on boundary conditions. Boundary conditions will include the extant of available job resources, the severity of the stressor (load versus overload), and occupation. Finding boundary conditions rather than generalisable effects of challenge stressors requires a refinement of the challenge–hindrance stressor framework by taking additional constructs (such as job resources) into account.

Theoretical background and hypotheses

Definition of challenge stressors

In their initial definition of challenge stressors, Cavanaugh et al. (1998, 2000) argued that challenge stressors result in the experience of stress but are also associated with positive outcomes. Such positive outcomes are to be expected if stressors are not only resource-depleting but also offer potential gains for individuals (see, e.g. O'Brien & Beehr, 2019). In reference to Hobfoll's (1989) idea of resource gains, Cavanaugh et al. (1998) contended that challenge stressors have positive outcomes because they offer a net gain in resources. This may be because these stressors are perceived as intrinsically rewarding experiences or because they contribute to learning and personal development (Cavanaugh et al., 1998). Thus, in this study, we will consider learning, motivation, and strain as potential outcomes of workload and cognitive demands.

Challenge stressors were initially operationalised by workload (together with time pressure, pressure to complete tasks, and time urgency) and job responsibility and were assessed in a sample of managers (Cavanaugh et al., 2000). Subsequent works have also considered job complexity (LePine et al., 2004); emotional demands (Bakker & Sanz-Vergel, 2013; Van den Broeck et al., 2010); and the level of attention required by job or role demands (Crawford et al., 2010) as challenge stressors. However, the main challenge stressors considered in the literature can be categorised as workload, cognitive demands, and job responsibility (Crawford et al., 2010; LePine et al., 2005). Workload refers to the volume of work and results from a mismatch between the amount of work to be done and the time available to complete it (Kristensen et al., 2004; Spector & Jex, 1998). Cognitive demands refer to the complexity of work and the amount of processing, problem-solving, and decision-making it involves.

The present meta-analysis will focus on workload and cognitive demands, due to the lack of a sufficient number of studies on job responsibility and learning.[1]

Relationships among workload, cognitive demands, and work outcomes

Workload, cognitive demands, and learning

The idea that work influences learning is longstanding. For instance, Hackman and Oldham (1976) hypothesised that challenging (i.e. cognitively demanding) jobs stimulate learning. In the same way, Karasek and Theorell's (1990) active learning hypothesis proposed that job demands create problems that must be resolved by employees and thus contribute to learning. Additionally, action regulation theory offers a detailed description of why, how, and when work characteristics result in learning (Frese & Zapf, 1994; Zacher, 2017; Zacher & Frese, 2018), therefore providing insights into the mechanisms linking work characteristics to learning. Based on these theoretical accounts, Parker (2014, 2017) recently proposed viewing learning, in addition to motivation and health, as a proximal outcome of work design.

According to Jacobs and Park (2009), workplace learning refers to “the many ways that employees learn in organizations” (p. 134). This learning in the workplace can take various forms. It can occur either in the realm of formal training and development or informally in the process of conducting one’s work (Manuti et al., 2015). The focus of the present meta-analysis is on informal learning because it accounts for up to 75% of the learning at work and should be more strongly related to work stressors than participation in formal programmes (Noe et al., 2014).

The challenge–hindrance stressor framework posits that learning in the workplace is promoted by challenge stressors (LePine et al., 2005). Notably, however, this framework does not provide a detailed description of how or why challenge stressors are conducive to learning. Furthermore, this assumption can be challenged both on empirical and theoretical grounds for at least certain challenge stressors. For instance, empirical evidence suggests that workload does not promote learning, whereas cognitive demands do (Glaser et al., 2015). Theoretically, these findings could be explained by drawing from the task-related learning model (Wielenga-Meijer et al., 2010; see also Taris & Kompier, 2005), which builds on action-regulation theory (Frese & Zapf, 1994; Hacker, 2003; Zacher & Frese, 2018).

The task-related model of learning (Wielenga-Meijer et al., 2010) differentiates between learning antecedents, learning processes, and learning consequences. Learning antecedents refer to task characteristics such as job demands or work stressors – in terms of the challenge–hindrance stressor framework – that are linked to learning consequences via learning processes. Learning consequences are the relatively stable changes in skills and knowledge that result from experiences made at work (Wielenga-Meijer et al., 2010). Thus, the focal learning consequence in the model is the “acquisition and automatizing of skills and knowledge” (Wielenga-Meijer et al., 2010, p. 364). Learning processes entail motivational processes (such as the willingness to learn), (meta-)cognitive processes (such as the construction of mental models or setting goals), and behavioural processes (such as exploration behaviour). Based on this model, we focused on skill and knowledge acquisition as learning consequences, proposing that the two challenge stressors of workload and cognitive demands are differentially related to these learning consequences.

Specifically, we argue that both (meta-)cognitive and behavioural learning processes are restricted by high levels of workload. Workload directs an individual’s focus to short-term performance gains and away from learning activities, as it imposes additional burdens on employees and can instill feelings of urgency and overload (Beck & Schmidt, 2013; Spector & Jex, 1998; Beck et al., 2017). If employees feel that their resources are threatened, they will likely try to conserve them (Hobfoll, 1989). Learning, however, builds on cognitive and behavioural processes – such as seeking feedback, exploration, reflection, and experimentation – that initially consume resources and yield benefits only with the passage of time (Ahearne et al., 2010; Frese & Zapf, 1994; Parker, 2017; van Ruysseveldt & van Dijke, 2011). This conflict between learning behaviours and short-term task progression is well documented in empirical work (for a review, see Soderstrom & Bjork, 2015). Thus, employees facing large workloads might feel that they do not have sufficient resources to engage in learning activities and choose to focus on strategies leading to immediate task progress (Beck & Schmidt, 2013; Kc et al., 2020). Instead of exploring new action plans, workers carrying great workloads will rather exploit existing skills and knowledge (Greco et al., 2019). For example, such workers have little opportunity for setting new goals, developing new action plans, or constructing appropriate mental models and tend to rely on previously automatised skills (Frese & Zapf, 1994; Taris & Kompier, 2005). As a result, they should be less likely to learn and develop new skills and competencies. Consequently, predictions derived from the task-related model of learning and action-regulation theory contradict propositions of the challenge–hindrance stressor framework and suggest workload to be negatively related to learning. We therefore present the following hypothesis:

Hypothesis 1: Workload is negatively related to learning.

Cognitive demands, on the other hand, are beneficial to (meta-)cognitive and behavioural learning processes and have even been described as important prerequisites for learning in action-regulation theory (Frese & Zapf, 1994; Zacher & Frese, 2018). Only tasks with sufficient complexity enable crucial learning behaviours, such as exploration, reflection, and experimentation (Frese & Zapf, 1994). In contrast, tasks that are highly structured and predefined do not offer enough opportunities to engage in such behaviours. Furthermore, cognitive demands stimulate (meta-)cognitive processes such as independent and creative thinking, as they often require employees to find solutions to new problems (Campbell, 1988; Glaser et al., 2015). Problem-solving requires employees to actively construct meaningful representations, such as coherent mental models (Seel et al., 2009). These behaviours and processes are known to promote learning and the acquisition of new skills and knowledge in employees (Daniels et al., 2009; Schooler, 1984). In line with the challenge–hindrance stressor framework, we therefore expect cognitive demands to be positively related to learning.

Hypothesis 2: Cognitive demands are positively related to learning.

Workload, cognitive demands, and motivation

In addition to learning-related processes, challenge stressors have the potential to elicit beneficial effects on work motivation. Work motivation refers to the affective, behavioural, and cognitive processes and actions that people direct toward achieving work-related goals (Kanfer & Chen, 2016). Because workers often perceive challenge stressors as obstacles that, if overcome, could augment goal achievement, pride, or feelings of competence, challenge stressors elicit positive emotions and active coping styles. Consequently, they contribute to work motivation (LePine et al., 2005; Van den Broeck et al., 2010).

According to the challenge–hindrance stressor framework (Crawford et al., 2010), workload should increase employees' efforts to manage the amount of work and direct their focus toward task progress (Kc et al., 2020). As employees perceive that it is important to meet heavy workloads, they are willing to invest effort even if they recognise that doing so will drain their resources and is associated with strain. The effort applied to a task has an activating and a directive role in motivation: it increases resources and may be used to more effectively manage work (Hockey, 1997). Supporting the assumption that workload has a motivational effect, Crawford et al. (2010) showed in a meta-analytical study that time urgency and workload were positively associated with work engagement.

Cognitive demands, on the other hand, should be motivating because they convey meaning and foster employees' feelings of competence. In turn, employees should be more willing to engage themselves in cognitive demands because they perceive meeting these demands as interesting and challenging (Crawford et al., 2010). Moreover, cognitive demands, such as problem-solving, can afford employees with opportunities to demonstrate and strengthen their sense of competence on the job (Deci & Ryan, 2000). Supporting these lines of reasoning, Schneider et al. (2017) found cognitive demands to be positively related to work engagement, an indicator of work motivation. This result corresponds with the finding that a combined measure of job demands that included workload and aspects of cognitive demands – such as job complexity and attention required by job demands – was positively linked to work engagement (Crawford et al., 2010). Together, these findings suggest that workload and cognitive demands are both positively associated with indicators of feeling motivated at work, such as work engagement, job motivation, dedication, and intrinsic motivation. In line with this earlier work on the challenge–hindrance stressor framework, we therefore predicted that both workload and cognitive demands would be positively related to work motivation.

Hypothesis 3: (a) Workload and (b) cognitive demands are positively related to work motivation.

Workload, cognitive demands, and strain

According to the challenge–hindrance stressor framework, challenge stressors require coping processes that consume workers' resources and result in psychological strain (e.g. Crawford et al., 2010; Mazzola & Disselhorst, 2019). Psychological strain refers to negative reactions, such as exhaustion, anxiety, or depression, that workers experience when they are exposed to work stressors (Sonnentag & Frese, 2003). These strains can result from resource depletion associated with workload as well as cognitive demands. Regarding workload, employees must invest additional effort in their work to meet performance requirements (Hockey, 1997) – for example, by working harder, resisting distractions, or increasing their pace when working on tight deadlines (e.g. Prem et al., 2017). Similarly, coping with cognitive demands may require an investment of effort. When solving complex problems, employees must invest cognitive resources and persist after initial setbacks, which may evoke negative reactions, such as exhaustion (Frese & Zapf, 1994). Supporting this line of argument, cognitive demands have been shown to be associated with feelings of fatigue (Meyer & Hünefeld, 2018). Because of the resource-depleting effects of both workload and cognitive demands, we anticipated that these factors would be positively related to strain.

Hypothesis 4: (a) Workload and (b) cognitive demands are positively related to strain.

Moderating effects of job control

Several models of work-related stress and well-being posit that the detrimental and beneficial effects of work stressors depend on the resources available for a particular job. The Job Demand-Control model (Karasek & Theorell, 1990), as well as the Job Demands-Resources model (Bakker & Demerouti, 2014), suggest that job resources, such as job control, provide the necessary conditions to perceive work stressors as motivating challenges and to effectively cope with stressful situations. Job control, the most widely studied job resource, refers to the discretion employees have in deciding when and how they perform their work (Karasek & Theorell, 1990). This is assumed to strengthen the motivating effect of challenge stressors because job control causes employees to feel that they have the necessary resources to effectively respond to work stressors. It has also been discussed as an important pre-requisite for learning as it allows employees to apply different skills and knowledge and so strengthen their expertise (Parker et al., 2021). Moreover, job control has been argued to buffer the strenuous effects of work stressors because it provides employees more opportunities to cope with stressful situations (Bakker & Demerouti, 2014; Karasek & Theorell, 1990). For these reasons, job control might moderate the effects of challenge stressors on motivation, learning, and strain (Bakker & Demerouti, 2014).

> Research Question 1: Does job control moderate the relationship between workload and cognitive demands on the one hand and learning, motivation, and strain on the other hand?

Moderating effects of operationalization

Edwards et al. (2014) argued that the perception of a stressor as challenging and its association with positive outcomes may be at least partially influenced by the severity of the stressor. In a similar vein, Karasek and Theorell (1990) stated that learning will occur in active jobs where job control is high and "psychological demands" (such as workload) "are also high but not overwhelming" (p. 34; as cited in Wielenga-Meijer et al., 2010, p. 363). Taking up this line of reasoning, O'Brien and Beehr (2019) recently pointed out that the severity of the challenge stressor workload might be reflected in its operationalisation. Although some measures of workload concern the amount of load, others focus on the aspect of being overwhelmed by asking about overload or carrying too heavy a load. Contingent on their operationalisation (i.e. load versus overload), stressors, which seem very similar, may thus have very different effects. Specifically, O'Brien and Beehr (2019) suggested that workload in the sense of load might act as a challenge stressor, arguing that it should be seen as a challenge that can be overcome through increased effort and that offers potential gains for the individual. The notion of "too much" that is contained in the concept of overload, however, ultimately indicates a hindrance to personal gain. Therefore, only workload – not overload – might demonstrate the beneficial effects of a challenge stressor and contribute to motivation. However, it is unclear whether such a nuanced difference can be empirically observed; after all, there is likely a considerable overlap between these two concepts. Therefore, this study examined on an exploratory basis whether the relationships between learning, motivation, and strain differed for the operationalisation of workload.

> Research Question 2: Does the operationalization of workload (overload vs. load) moderate the relationship between workload on one hand and learning, motivation, and strain on the other?

Moderating effects of occupation

Studies on the challenge–hindrance stressor framework have often been criticised for assuming that all workers experience stressors in similar ways and not taking interpersonal differences into account (e.g. Mazzola & Disselhorst, 2019; Webster et al., 2011). According to role theory, the way that a stressor is appraised will depend on occupational role expectations (Kahn et al., 1964; Semmer et al., 2015). The challenge–hindrance stressor framework was originally developed and tested using a sample of managers (Cavanaugh et al., 2000), for whom workload could be considered part of their occupational role and thus be associated with potential gains, such as a sense of delight (see e.g. Aubert, 2009). However, for occupations involving care and relationship-building (e.g. nurses or social workers), a heavy workload might be viewed as an obstacle to fulfilling one's occupational role (Bakker & Sanz-Vergel, 2013; Semmer et al., 2015). This could explain why workload has not been shown to have a motivating effect among care or social workers (Bakker & Sanz-Vergel, 2013). Therefore, this study tested whether the occupation types of a sample moderated the relationships between workload and cognitive demands with learning, motivation, and strain. We focused on care and social workers and compared them to all other samples as it allowed us to build on the work of Bakker and Sanz-Vergel (2013). We also chose this occupation type as there is a high number of studies on care and social workers and in many of them large parts of the sample are recruited from this population. This makes it well suited for sub group analysis as it provides such an analysis with the necessary statistical power.

> Hypothesis 5: The occupation of the sample (care and social workers vs. all other samples) will moderate the relationship between workload and motivation. The relationship will be negative for care and social workers and positive for all other samples.

For all other relationships, this study examined moderating effects of the type of sample on an exploratory basis.

> Research Question 3: Does the occupation of the sample (care and social workers vs. all other samples) moderate the relationships between workload and learning and strain and between cognitive demands and learning, motivation, and strain?

Method

Literature search

First, we conducted keyword searches in the databases Web of Science and PsycINFO. We used keywords for either cognitive demands (e.g. job complexity, mental demands) or workload (e.g. time pressure, work overload, quantitative demands), which were paired with additional keywords for motivation, strain, or learning (e.g. cognitive demands AND motivation). Furthermore, we searched databases with unpublished studies, including the Conference Proceedings Citation Index (CPCI) and Dissertation Abstracts International (A and B). We narrowed this search by adding keywords related to work (e.g. "job" or "occupational") and focusing on relevant categories in the Web of Science (e.g. "psychology" or "management"; see supplementary materials for all keywords used). Second, we carefully reviewed the reference lists of previous meta-analyses (e.g. Crawford et al., 2010; LePine et al., 2005; Lesener et al., 2018). Third, we performed a forward citation search of major measurement source articles (e.g. Bakker et al., 2003; van Veldhoven & Meijman, 1994) using the databases Web of Science, PsycINFO, and Google Scholar. After removing duplicates, this search strategy yielded 6152 articles. Using these 6152 articles as input, we manually screened title and abstracts for relevance using the Covidence software (Veritas Health Innovation, 2018) and identified 1299 potentially relevant studies that were eligible for further screening.

Inclusion criteria

We assessed the full text of the 1299 studies that remained after the initial eligibility screening. A study was eligible for inclusion if it met the following criteria:

(a) It included at least one measure of either cognitive demands or workload and one measure of the dependent variables strain, motivation, or learning;

(b) It provided at least one correlation coefficient with sample size between one of the demands and one of the dependent variables. When no correlation coefficient was reported, efforts were made to contact the authors to obtain the missing information;
(c) The sample was drawn from the healthy working population. This excluded samples of volunteers or nonworking students. Self-employed individuals were excluded because they differ markedly from employees in terms of a number of job characteristics, including job autonomy and job insecurity (Hessels et al., 2017; Millán et al., 2013; Nordenmark et al., 2012);

(d) It was a field study. Studies that used a laboratory experiment design or a vignette design were excluded;[2] and
(e) It was published in either English or German.

Applying these inclusion criteria, we excluded 911 records, resulting in a final database of 388 articles and studies, which included both published and unpublished work (including dissertation theses, conference proceedings, and unpublished data).

Coding of studies

For each study, we coded the constructs measured; the scales used and their reliabilities; correlation coefficients and corresponding sample size; study design; type of sample; age (*M* and *SD*); gender; country of data collection; year of data collection; and type of publication. If a study contained multiple independent samples, the correlations were obtained from each sample and subsequently treated as independent samples. For longitudinal studies, we coded the correlations within time points (cross-sectional correlations) using the time point with the largest sample size. If this information were not available, correlations were coded between time points. For diary studies, we coded the correlations from the general questionnaire or the between-person correlations (as previously done by Wendsche & Lohmann-Haislah, 2017). If this information were not available or if the authors could not be contacted, the study was eliminated.

The studies were coded by the first, second, and last authors of this study and by two psychology master's students who had received extensive training. Coding decisions were continuously discussed in meetings and via email. In order to assess interrater agreement, two raters coded more than 10% ($n = 53$) of the studies. The raters agreed on 93% of the coding decisions, and all discrepancies were resolved by reviewing the disputed study again. Ultimately, this meta-analysis included correlations from 388 studies with 417 independent samples.

Categorisation of challenge stressors and outcomes

Workload. This category included measures that captured quantitative aspects of workload, such as quantitative demands, time pressure, or work overload. Scales that contained items regarding demands beyond workload were not included. For studies using the Job Content Questionnaire (JCQ; Karasek et al., 1998; Karasek, 1985; Karasek & Theorell, 1990), we attempted to contact the authors to obtain information about the specific content of the items used, as the original scale contained one item regarding conflicting demands. We only included studies if this specific item were not used, as conflicting demands are not necessarily related to workload and are also more consistent with the definition of a hindrance stressor. This study considered both objective (e.g. caseload) and self-reported measures of workload.

Cognitive demands. This category included measures capturing the cognitively demanding aspects of jobs, such as job complexity, problem-solving demands, and mental demands. We considered both objective measures (e.g. jobs rated using the Dictionary of Occupation Titles) and self-reported data.

Strain. This category included measures of psychological strain, which typically results from prolonged expenditures of effort or experiences of distress (Lazarus & Folkman, 1984; LePine et al., 2005), such as exhaustion, burnout, fatigue, irritation, depression, and anxiety.

Motivation. This category included measures that captured states of motivation at work, including work engagement, job motivation, dedication, and intrinsic motivation.

Learning. This category included scales that explicitly measured learning, the acquisition of competencies or skills, or personal development at work. We also included scales measuring opportunities to learn at one's job, as this has been shown to be a valid and proximal indicator of actual learning on the job (van Ruysseveldt & Taverniers, 2010, as cited in van Ruysseveldt et al., 2011). Further, the items of scales measuring opportunities to learn often refer directly to learning as a consequence of the job (e.g. "Do you learn new things in your work" from the Questionnaire on the Experience and Evaluation of Work; van Veldhoven & Meijman, 1994).

Moderator variables

As the majority of the studies considered did not include product terms for *job control* and motivation, learning, or strain, we relied on country-level data to test the moderating effect of job control (for a similar approach, see Guthier et al., 2020). We used the standardised country-level data on job control of the surveys from 2005 and 2015 by the International Social Survey Programme Work Orientations (ISSP Research Group, 2013, 2017). The International Social Survey Programme is a standardised social science survey that collected data in 2005 and 2015 with representative samples from

44 countries. For each of these samples, the respective country mean of job control of the ISSP Work orientations survey was coded. Job control was measured using one item, which asked how free the person was to decide how their work was organised.[3] For samples that were published in or before 2009, data from the ISSP 2005 was used. For these samples, the mean publication year was 2007. Samples that were published during or after 2010 were coded with the data from the ISSP 2010. The mean publication year for these samples was 2011. If there were only country-level data available for one survey (2005 or 2015), the available data was used. For this analysis, we were able to code country-level data of job control for 336 samples (80.38% of all samples included) coming from 32 countries.

To test whether the *operationalisation of workload* affected the relationship between workload and outcomes (O'Brien & Beehr, 2019), we coded whether studies used measures of overload or measures of load. Measures of overload included work, role, or quantitative overload. Measures of load were workload, quantitative demands, time pressure, and similar factors. An example item for measuring overload is "I have so much work to do, I cannot do everything well," from the scale of Cammann et al. (1983), and a sample item for measuring load is "How often does your job require you to work very fast?" from the Quantitative Workload Inventory by Spector and Jex (1998). Overall, 73 samples (17.51% of all samples included) used measures of overload, providing 113 effect sizes.

To test the moderator effects of the *occupation of the sample*, we coded whether the main task of a given sample involved care or social work (e.g. nurses, doctors, social workers). Notably, this distinction was made only if it applied to at least 75% of the sample. In total, 120 samples (28.71% of all samples included) were coded as care or social workers and their samples provided 214 effect sizes.

Description of analyzed studies

In total, this analysis comprised 388 studies with 417 samples and a total sample size of $N = 319{,}306$ participants, with an average sample size of $N = 767.35$. Together, the included studies provided 781 effect sizes. The majority of these comprised effect sizes in which both variables were measured at the same time point ($k = 707$; 90.52% of all effect sizes). For 22 samples (2.82% of all samples) the predictor and the criterion variable were measured with a time lag between them. In addition, 53 (6.67%) of the effect sizes were sourced from diary studies. Of these, 52 samples comprised between-person correlations and one sample a within-person correlation. All studies were published in English, except for one study, which was published in German.

Cognitive demands were part of 182 effect sizes. Of these, 169 used a self-reported measure, and 13 used other-reported or objective measures for cognitive demands. Workload was part of 533 relationships. Here, 522 relationships were based on self-reported measures for workload, and 9 were other-reported or objective measures. Motivation was part of 213 relationships, with all except for one study using self-reported measures. For learning, 96 effect sizes were analyzed, and all of them used a self-reported measure for learning. For strain, 539 relationships were included, and all of them used self-reported measures. Table A in the supplementary materials summarises all of the information from the studies included in the analysis. Information on the moderator variables can be found in Table B in the supplementary materials. Furthermore, all coded information of the primary studies is available under this heading: https://osf.io/phjyv.

Meta-analytic procedures

First, we conducted random-effects psychometric meta-analysis as described by Schmidt and Hunter (2015), using the psychmeta R package (Dahlke & Wiernik, 2019; Version 2.3.4). Each correlation was corrected for sampling and measurement error in the criterion and predictor using the reported Cronbach's alphas. If a study reported multiple indicators for the same overall construct, we computed composite correlations using Hunter and Schmidt's (2004) composite formula. When no reliability was reported, we used the mean reliability of all studies that reported reliabilities for the focal construct (Schmidt & Hunter, 2015). For single-item measures and objective measures (e.g. caseload), we set reliability at 0.70 and 1.00, respectively (Wanous & Hudy, 2001; see also Swider & Zimmerman, 2014).

We computed mean observed correlation coefficients (r), mean corrected correlations (ρ), and 95% confidence intervals (CIs) around the mean corrected correlations. A CI excluding zero suggested that the mean population correlation was significantly different from zero ($p < 0.05$).

To examine heterogeneity, we calculated 80% credibility intervals (CRs) around the mean corrected correlations. The CR specifies the range within which 80% of the values in the ρ distribution fall and is therefore important in evaluating a relationship's generalizability (Schmidt & Hunter, 2015). High heterogeneity in correlations between studies is represented by wide CRs, indicating that the nature of the relationship is likely dependent on moderators, such as sample and study characteristics. Narrow CRs indicate that potential moderator variables can have only small effects. In addition to the absolute width of CRs, meaningful heterogeneity is also determined by the range of effect sizes a CR is spanning (Wiernik et al., 2017). CRs that range from small effect sizes to large effect sizes indicate greater heterogeneity than CRs that include effects of similar size at the upper or lower ends (Wiernik et al., 2017).

To interpret effect sizes and CRs, we used the method by Wiernik et al. (2017) and compared our results to Paterson et al.'s (2016) empirical distribution of corrected correlations of over 250 meta-analyses of organisational behaviour. According to the quartiles of the distribution, we interpreted corrected correlations of $(\rho) < .15$ as negligible; $.15 < (\rho) < .24$ as small; $.25 < (\rho) < .39$ as moderate; and $(\rho) > .40$ as large. CRs that spanned a large part of the distribution (e.g. from "small" to "large") were interpreted as reflecting meaningful heterogeneity in effect sizes (Wiernik et al., 2017; see also Wiernik & Kostal, 2019). We also report I^2, which is an index of the proportion of variance that is not explained by sampling error, and τ^2, which is an estimate of the random effects variance, as additional measures of heterogeneity. However, to evaluate heterogeneity in effect sizes, we focused on credibility intervals, as their interpretation is less ambiguous (Schmidt & Hunter, 2015). Further, we followed the recommendations by Schmidt and Hunter (2015) and did not use the Q test to assess heterogeneity. The Q test tends to have low power to detect moderator effects if the number of studies is small (Hedges & Pigott, 2001). On the other hand, if the number of studies is large, trivial heterogeneity can lead to a significant Q test, even if heterogeneity is not practically meaningful (Schmidt & Hunter, 2015).

We then performed a random effects meta-analytic path analysis using two-stage structural equation modelling to test our hypotheses (TSSEM; Cheung, 2014; Cheung & Chan, 2005). This was deemed appropriate to account for the high intercorrelations between the two predictors (workload and cognitive demands). In this approach, correlation coefficients are first pooled using multigroup structural equation modelling (Stage 1). Next, the resulting pooled correlation coefficients matrix is used to fit a structural model employing weighted least squares estimation (Stage 2). This procedure ensures that parameters that are estimated with greater precision due to larger number and size of studies are assigned more weight in the estimation of model parameters (Cheung & Chan, 2005; Jak, 2015). For Stage 1, the study correlation coefficients were used as input after correcting them for measurement error. The TSSEM analyses were conducted using the metaSEM R package (Cheung, 2015), following the instructions of Cheung (2014) and Jak (2015). As all paths were specified, we had a saturated model which fitted the data perfectly. Thus, we do not report fit statistics.

To test the moderating effect of job control, we conducted a three-level meta-analysis, as the data structure was hierarchical, with study participants (Level 1) nested within samples (Level 2), which were nested within countries (Level 3). To account for this dependency, a three-level model was fitted using the R package metafor (Viechtbauer, 2010). Next, variances and effect sizes were calculated and corrected for measurement error using the psychmeta package and then used as input to fit the three-level model with metafor.

Moderator effects of operationalisation of workload and occupation were tested with subgroup analysis using the bivariate correlations between stressors and outcomes. This approach is recommended for dichotomous moderator variables (Schmidt, 2017). To assess whether the effect sizes differed between the subgroups, we constructed a 95%-CI around the difference between the true correlation (Olkin & Finn, 1995; Zou, 2007). Differences were deemed significant when the CIs did not include zero.

Results

Meta-analytic results for the bivariate relationships between all variables as well as subgroup analyses are reported in Table 1. Workload showed no significant relationship with learning, $\rho = -.06$; 95% CI [−.12 to .001], a weak negative relationship with motivation, $\rho = -.06$; 95% CI [−.10 to −.03], and a significant and strong relationship with strain, $\rho = .42$; 95% CI [.40 to .44]. Cognitive demands showed a strong positive relationship with learning, $\rho = .47$; 95% CI [.32 to .62], and moderate positive correlations with motivation, $\rho = .21$; 95% CI [.12 to .29] and strain, $\rho = .22$; 95% CI [.18 to .26].

To test our hypotheses, we will focus on the results of the meta-analytic path model, as we are interested in the unique relationships of workload and cognitive demands with all three outcomes. A summary of the results of the meta-analytic path model is provided in Figure 1.

For workload, we found negative associations with learning, $\beta = -0.35$, with likelihood-based 95% CI (LBCI) [−0.50 to −0.21] and motivation, $\beta = -0.14$; LBCI [−0.23 to −0.06] and a positive association with strain, $\beta = 0.45$; LBCI [0.40 to 0.50]. Therefore, Hypothesis 1 was supported, Hypothesis 3a was rejected, and Hypothesis 4a was

Table 1. Bivariate meta-analytic results.

	k	N	r	SD_r	ρ	SD_ρ	95% CI	80% CV	I^2	τ^2
Workload – learning	32	90,688	−.05	.13	−.06	.17	[−.12, .00]	[−.27, .16]	98.04	0.03
Cognitive demands – learning	17	13,345	.37	.23	.47	.29	[.32, .62]	[.08, .86]	98.21	0.09
Workload – motivation	96	99,309	−.05	.14	−.06	.17	[−.10, −.03]	[−.28, .15]	95.34	0.03
Cognitive demands – motivation	26	13,600	.17	.17	.21	.21	[.12, .29]	[−.07, .48]	94.03	0.04
Workload – strain	350	242,436	.35	.14	.42	.17	[.40, .44]	[.21, .63]	94.16	0.03
Cognitive demands – strain	84	73,493	.18	.16	.22	.20	[.18, .26]	[−.03, .47]	95.94	0.04
Workload – cognitive demands	55	26,654	.41	.15	.52	.17	[.47, .56]	[.30, .73]	92.22	0.03
Motivation – learning	16	51,034	.50	.12	.61	.15	[.53, .69]	[.41, .81]	98.82	0.02
Motivation – strain	74	72,508	−.41	.22	−.46	.26	[−.52, −.40]	[−.79, −.13]	98.61	0.07
Learning – strain	31	61,389	−.27	.24	−.33	.30	[−.44, −.22]	[−.73, .06]	99.26	0.09

Note: k = number of samples included in meta-analysis, N = total sample size, r = mean observed correlation, SDr = standard deviation of observed correlations, ρ = mean corrected correlation, $SD\rho$ = standard deviation of corrected correlations after removing sampling and measurement error, 95% CI = 95% confidence interval for ρ, and 80% CV = 80% credibility interval for ρ, I^2 = estimated percentage of variability not caused by sampling error and artifacts, τ^2 = estimated random-effects variance

supported. Cognitive demands showed positive relationships with learning, $\beta = 0.60$; LBCI [0.41 to 0.80] and motivation, $\beta = 0.26$; LBCI [0.16 to 0.38], and a negative relationship with strain, $\beta = -0.07$; LBCI [−0.15 to −0.0003]. This supported Hypotheses 2 and 3b and rejected Hypotheses 4b. The model explained 27.54% of variance in learning, 5.21% of variance in motivation, and 17.42% of variance in strain.

Moderator analysis

The meta-analytic results showed considerable heterogeneity in most of the relationships of stressors with outcomes, which suggests the presence of moderator variables. The highest amounts of meaningful heterogeneity were found for the relationships of workload with learning and motivation, with 80% credibility intervals spanning from

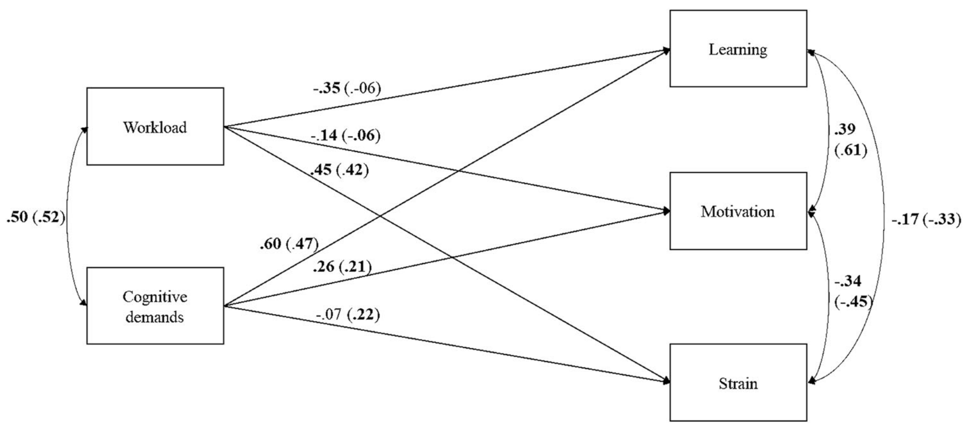

Figure 1. Summary of the meta-analytic results with estimates of meta-analytic path modelling and bivariate relationships.

Note: Values are standardised estimates for meta-analytic path modelling and mean corrected correlations ρ for the bivariate relationships. Total N = 319,306. All values in bold are significant at $p < .05$.

moderate negative effects to negligible-to-small positive effects. For the relationships of cognitive demands with motivation and strain, 80% credibility intervals spanned from negligible negative effects to large positive effects. More consistent effects were found for the relationships of cognitive demands with learning and for workload with strain: The 80% credibility intervals for the relationship between cognitive demands and learning were consistently positive and spanned from negligible positive to very large positive effects. For workload and strain, 80% credibility intervals spanned from moderate positive to large positive effects.

We tested for moderator effects of job control using country-level data for each sample when available. The results are shown in Table 2. Due to the small number of studies and countries for some of the relationships, only the results for the relationships of cognitive demands and strain, workload and motivation, and workload and strain should be interpreted (Schmidt, 2017). No significant moderating effects of job control on any of the examined relationships were found.

We also tested whether the operationalisation of workload moderated the relationship between workload and outcomes. Specifically, we compared the relationships between workload and outcomes in studies measuring overload vs. those measuring load. The results are shown in Table 3. The negative relationship between measures of overload and motivation was stronger, $\rho_{overload} = -.11$, than the relationship between measures of load and motivation, $\rho_{load} = -.04$, but the difference between the effect sizes was not significant, as the confidence interval for the difference included zero, $\rho_{delta} = .07$; 95%-CI [.15 to −.01]. Measures of overload showed a stronger negative relationship with learning, $\rho_{overload} = -.19$ than measures of load, $\rho_{load} = -.03$, with a significant difference between effect sizes, $\rho_{delta} = .16$; 95%-CI [.24 to .08]. In addition, we found a significantly stronger relationship between strain and overload, $\rho_{overload} = .48$, than between strain and load, $\rho_{load} = .41$; $\rho_{delta} = .07$; 95%-CI [.03 to .11]. The credibility intervals for relationships with measures of overload reflected less heterogeneity than those for the relationships with measures of load. In summary, measures of overload showed stronger and more consistently unfavourable relationships with learning and strain than measures of load.

Finally, we tested for moderating effects of occupations of the sample. Results of the subgroup analysis are shown in Table 3. The negative relationship between workload and motivation was higher for care and social worker samples, $\rho_{care} = -.14$, than for all other

Table 2. Estimates for job control as a moderator of the relationships between stressors and outcomes.

Relationship	k	$N_{countries}$	B	SE	t	p-value	95% CI	Study level (Level 2) variance in %	Country level (Level 3) variance in %
Workload – motivation	82	20	0.19	0.29	0.66	.51	[−0.39, 0.77]	90.39	6.78
Workload – strain	281	30	0.11	0.17	0.64	.52	[−0.22, 0.43]	94.15	2.25
Cognitive demands – strain	71	16	−0.25	0.44	−0.57	.57	[−1.14, 0.63]	64.20	33.02
Workload – learning	28	12	−0.64	0.48	−1.33	.19	[−1.63, 0.35]	98.98	0.00
Cognitive demands – motivation	21	9	0.63	0.64	0.99	.33	[−0.71, 1.98]	94.12	0.00
Cognitive demands – learning	11	5	−0.82	3.39	−.24	.81	[−8.49, 6.85]	83.90	15.12

Note: Due to the low number of studies and countries, results should not be interpreted for the relationships of workload with learning and cognitive demands with motivation and learning. k = number of studies; $N_{countries}$ = number of countries; B = unstandardized/raw regression coefficient; SE = standard error (robust); t = t statistic; * $p < .05$; 95% CI = 95%-confidence intervals.

Table 3. Results for subgroup analyses.

	k	N	r	SD_r	ρ	SD_ρ	95% CI	80% CV	I^2	τ^2
Workload – learning										
Load – learning	26	72,262	−.03	.14	−.03	.17	[−.10, .04]	[−.25, .19]	98.12	0.03
Overload – learning	6	18,426	−.14	.04	−.19	.06	[−.24, −.13]	[−.26, −.11]	83.15	0.003
Care and social worker samples	9	16,434	−.12	.06	−.15	.08	[−.21, −.09]	[−.26, −.05]	87.19	0.01
Other samples	23	74,254	−.04	.14	−.04	.17	[−.11, .04]	[−.27, .19]	98.44	0.03
Cognitive demands – learning										
Care and social worker samples	4	2888	.07	.17	.08	.22	[−.27, .44]	[−.27, .44]	95.44	0.05
Other samples	13	10,457	.45	.16	.58	.21	[.45, .71]	[.29, .86]	97.17	0.04
Workload – motivation										
Load – motivation	79	70,451	−.04	.15	−.04	.18	[−.08, −.00]	[−.27, .18]	95.09	0.03
Overload – motivation	17	28,858	−.09	.12	−.11	.14	[−.18, −.04]	[−.30, .07]	95.83	0.02
Care and social worker samples	26	21,563	−.12	.11	−.14	.13	[−.19, −.09]	[−.30, .02]	90.57	0.02
Other samples	70	77,746	−.04	.15	−.04	.17	[−.08, −.00]	[−.27, .18]	95.82	0.03
Cognitive demands – motivation										
Care and social worker samples	3	3198	.20	.14	.28	.20	[−.22, .77]	[−.09, .65]	95.58	0.04
Other samples	23	10,402	.16	.19	.19	.22	[.10, .29]	[−.09, .48]	93.93	0.05
Workload – strain										
Load – strain	284	19,652	.34	.14	.41	.17	[.39, .43]	[.20, .61]	93.94	0.03
Overload – strain	66	45,916	.39	.13	.48	.16	[.44, .52]	[.27, .69]	94.31	0.03
Care and social worker samples	107	56,722	.39	.13	.46	.15	[.44, .49]	[.28, .65]	91.20	0.02
Other samples	243	185,714	.34	.14	.41	.17	[.39, .43]	[.20, .62]	94.78	0.03
Cognitive demands – strain										
Care and social worker samples	19	10,818	.13	.12	.17	.15	[.10, .25]	[−.02, .36]	88.42	0.02
Other samples	65	62,675	.19	.16	.23	.20	[.18, .28]	[−.03, .49]	96.59	0.04

Note: k = number of samples included in meta-analysis, N = total sample size, r = mean observed correlation, SDr = standard deviation of observed correlations, ρ = mean corrected correlation, $SD\rho$ = standard deviation of corrected correlations after removing sampling and measurement error, 95% CI = 95% confidence interval for ρ, and 80% CV = 80% credibility interval for ρ, I^2 = estimated percentage of variability not caused by sampling error and artifacts, τ^2 = estimated random-effects variance.

samples, $\rho_{\text{other}} = -.04$, and the effect sizes differed significantly from each other, $\rho_{\text{delta}} = .09$; 95%-CI [.03 to .16]. Similarly, the negative relationship between workload and learning was stronger for care and social workers, $\rho_{\text{care}} = -.15$, than for all other samples, $\rho_{\text{other}} = -.04$ with effect sizes differing significantly from each other, $\rho_{\text{delta}} = .09$; 95%-CI [.02 to .20]. The positive relationship between strain and workload was stronger for care and social workers, $\rho_{\text{care}} = .46$, than for all other samples, $\rho_{\text{other}} = .41$, and there was a significant difference between effect sizes, $\rho_{\text{delta}} = .05$; 95%-CI [.01 to .09]. For all of the relationships between workload and outcomes, the CRs reflected less heterogeneity for care and social worker samples than for all other samples. Overall, workload showed stronger and more consistently unfavourable relationships with motivation, learning, and strain in the care and social worker samples than in other samples.

The relationships of cognitive demands with motivation and learning could not be interpreted, as there were too few studies in the respective subgroups to rule out sampling error. There were no marked differences in the relationship between cognitive demands and strain for care and social workers, $\rho_{\text{care}} = .17$, and all other samples, $\rho_{\text{other}} = .23$; $\rho_{\text{delta}} = .06$; 95%-CI [−.02 to .14], and heterogeneity was not substantially reduced in the subgroups.

Sensitivity analyses

We analyzed the relations of specific stressors with learning, motivation, and strain, to test whether our findings depended on grouping different stressors into workload and cognitive demands. We compared the relations of workload, quantitative demands, role overload, patient/case load, and work pressure with learning, motivation, and strain. The results suggest that quantitative demands are more clearly negatively related to motivation, while time pressure and work pressure showed non-significant or positive relations with motivation. However, the small number of studies, uneven distribution of studies across groups, and high heterogeneity in the effect sizes do not allow to draw definitive conclusion (Cuijpers et al., 2021; Schmidt & Hunter, 2015). For cognitive demands, we analyzed the relations of cognitive demands, mental demands, qualitative load, problem-solving demands, and job complexity with the outcomes separately. No significant differences in effect sizes were found or subgroup analysis was not possible for the different types of stressors. More detailed results can be found in the supplementary materials.

To investigate the potential influence of common method variance, we compared the relations between stressors and outcomes for studies with a cross-sectional design and for studies that used a time lag between measurements of stressors and outcomes. The main study conclusion did not depend on the study design, but subgroup analysis was often hindered due to the small numbers of studies per group. More detailed results can be found in the supplementary materials.

To further investigate the potential influence of common method variance, we examined whether relations with self-report measures would differ from relations using objective or other-rated measures. However, the small numbers of studies using objective or other-rated measures did not allow for subgroup analyses. Detailed information on the relations for different types of measures can be found in the supplementary materials.

To test for publication bias, we produced funnel plots for all of the analyzed relationships and conducted trim-and-fill analyses. Trim-and-fill analyses suggested substantial numbers of missing studies for the relationships of workload and motivation, cognitive demands and motivation, and cognitive demands and strain. Adding the missing studies did not alter study conclusions. Egger's regression tests (Egger et al., 1997) were non-significant for all of the relationships. More detailed results tests can be found in the supplementary materials.

To identify outliers, we used the diagnostic statistics provided by the *metafor* package in R (Viechtbauer & Cheung, 2010). These include DFFITS values, Cook's distances, hat value and DFBETAS. We identified various outliers. Excluding these studies led to non-significant relations of workload with motivation and learning. However, the results should be interpreted with caution, as outlier analyses in the case of meta-analyses has been described as problematic, as it is difficult to distinguish large sample errors from true outliers (Schmidt & Hunter, 2015). Detailed information on the studies identified as outliers and the computed correlations after excluding them can be found in the supplementary materials.

Discussion

This meta-analysis tested a central assumption of the challenge–hindrance stressor framework (Cavanaugh et al., 2000; Crawford et al., 2010), namely that challenge stressors

– besides being straining and motivating – promote learning. Building on action-regulation theory (Frese & Zapf, 1994; Zacher & Frese, 2018) we challenged this assumption and proposed that the challenge stressors of workload and cognitive demands differentially relate to learning, while uniformly relating to motivation and strain. To test these propositions, we moved beyond previous meta-analyses combining different challenge stressors in one category (LePine et al., 2005) and conducted a meta-analysis considering workload and cognitive demands as independent categories of challenge stressors. Doing so, allowed us to unmask differential relationships of workload and cognitive demands with learning. Results of our meta-analytic path model confirmed our key hypothesis, namely that workload and cognitive demands are differentially related to learning. Cognitive demands thus help while workload hinders workplace learning. Interestingly and contrary to expectations, cognitive demands and workload were also differentially related to motivation and strain. Mirroring findings for learning, workload was negatively while cognitive demands were positively related to motivation. For strain, the association with workload was positive and the association with cognitive demands was negative. Thus, neither of the two challenge stressors showed the association pattern predicted by the challenge–hindrance stressor framework. Before drawing general conclusions from these results, we discuss the individual results in more detail.

As expected based on action-regulation theory (Frese & Zapf, 1994), we found workload and cognitive demands to be differentially related to learning. This result contradicts the assumption of the challenge–hindrance stressor framework (Cavanaugh et al., 2000; Crawford et al., 2010; LePine et al., 2005) that all stressors currently referred to as challenge stressors contribute to learning. Rather, workload the most widely-studied challenge stressor, could impede learning by reducing opportunities for crucial learning behaviours, such as experimenting, exploring, and reflecting (Beck & Schmidt, 2013) that expand employees' knowledge into novel areas. Since acquiring new knowledge consumes time and energy, and there is no assurance that the new knowledge will be beneficial in the long run, employees facing high levels of workload may use such learning strategies less often. Cognitive demands, on the other hand, seem to motivate employees to invest learning effort as these demands expose information-knowledge gaps and require problem-solving (Hardy et al., 2019). To overcome knowledge gaps and to solve problems employees are likely to engage in exploration strategies. As a result, they acquire new skills, knowledge and insights.

Contrary to our expectations and to the predictions of the challenge–hindrance stressor framework (Cavanaugh et al., 2000; Crawford et al., 2010), we found a negative association between workload and motivation. This result contradicts earlier meta-analyses which showed workload to be positively related to motivation (Crawford et al., 2010; LePine et al., 2005). However, our meta-analysis expanded upon previous meta-analyses published a decade ago (Crawford et al., 2010) by including a substantially larger number of studies (i.e. 96 compared to 25 studies). The reason for this is the increased research interest in engagement, with the number of annual publications having increased steadily over the last two decades (Schaufeli et al., 2019). Substantially more studies have been published in the period after 2008, the date when Crawford et al. (2010) searched the literature, than before. This is reflected in this study's sample of studies on the relation between workload and motivation, including 76 studies published after 2008 and 20 studies published before 2008. Due to this larger sample the present meta-analysis should provide a more accurate assessment of the relationship between workload and motivation.

Recently, scholars have already raised doubts on the notion that workload fosters motivation (Baethge et al., 2018; Reis et al., 2017). In fact, there are various workload-related factors that could harm motivation. For instance, high workload puts high demands on an individual's capacity to process information and regulate goal progress (Frese & Zapf, 1994; Zacher & Frese, 2018). Such demands could be compensated for some time through higher activation but could ultimately cost too much effort to be sustained (Frese & Zapf, 1994). As a result, employees could disengage from their work (Hockey, 2013). Supporting this argument, Baethge et al. (2018) found positive effects of workload on engagement on a within-person level but negative effects on a between-person level. They conclude that momentary increases in workload could challenge and motivate employees but chronically high levels would rather lead to frustration and disengagement.

Furthermore, managing high workloads could be connected to trade-offs in quality. To meet high workloads, employees might reduce the quality of their task-performance which can lead to discontent about the work results and decreased motivation. Such negative effects of workload on motivation should be even stronger for certain occupations in which a particularly fast task completion conflicts more strongly with the quality of the work, such as in care and social work. In line with this argument, our moderator analysis revealed that workload is more strongly negatively related to motivation in samples of care and social workers than in other samples. Other moderators, such as the level of the stressor or job control did however not alter the strength of the relation. A possible explanation for not finding the moderation effect of job control is that job control was measured at the country level. Although there were significant differences in average job control across countries, it is likely that job control varies more strongly across occupations than across countries. As the samples for our meta-analysis included a broad range of different occupations, this could have confounded the effects of job control on the country level.

Contrary to expectations, we found a negative relationship between cognitive demands and strain. Comparing the bivariate correlation and the path coefficient reveals that the relationship between cognitive demands and strain only became negative after controlling for workload. This suggests that the stand-alone relationship between cognitive demands and strain may, in fact, be driven by high levels of workload that often go hand in hand with high cognitive demands.

Taken together, neither workload nor cognitive demands showed the pattern of relations proposed by the challenge–hindrance stressor framework. Workload was positively associated with strain but negatively associated with motivation and learning. In contrast, cognitive demands showed positive associations with motivation and learning and a negative association with strain. We draw two conclusions from these results. First, neither workload nor cognitive demands should be classified as challenge stressors. Workload was not associated with any beneficial outcomes and would thus rather fit the definition of a hindrance stressor. Cognitive demands on the other hand, showed a pattern more similar to a resource than to a stressor. Such a conceptualisation of cognitive demands is in line with early theories of work design, such as the Motivation-Hygiene Theory by Herzberg (1966) or the Job Characteristics Model by Hackman and Oldham (1976). These theories have put forward the motivating and beneficial, rather than the straining, effects of jobs that offer high complexity.

Second, it should be reconsidered whether there are stressors that do in fact show beneficial and detrimental effects simultaneously, as proposed by the challenge–hindrance stressor framework. Although we cannot rule out that other challenge stressors might affect employees in such a way, we could not find any evidence for such a pattern for two of the most prominent challenge stressors, workload and cognitive demands. For job responsibility, another often mentioned challenge stressor, we were not able to identify sufficient primary studies relating it to motivation, learning, and strain. This is an issue for future research to explore.

Future research should also consider to integrate the role of time in the challenge–hindrance stressor framework more carefully. We already tried to address this in our sensitivity analyses by comparing studies using a cross-sectional design with studies using a time-lag between measurements, but unfortunately there were too few studies with such a design to draw reliable conclusion. Issues of time are likely important determining factors on how stressors affect employees but they are often overlooked in theories of organisational behaviour (Shipp & Cole, 2015). Specifically, short-term and long-term dynamics should be disentangled in the challenge–hindrance stressor framework. Recent works by Baethge et al. (2018) and Rosen et al. (2020) have shown that this can be a promising avenue for the challenge–hindrance stressor framework to move forward. Challenge stressor could affect employees differently depending on whether they occur over a long period of time or are only present for a limited amount of time (Baethge et al., 2018) and also depending on whether they are foreseeable for employees or not (Rosen et al., 2020). Short-term increases in stressors allow employees to engage with the stressor but have a lower risk of frustrating or overwhelming employees. Foreseeable stressors give employees the opportunity to plan and prepare for the stressor and so maximise their beneficial effects (Rosen et al., 2020). Further, the consequences of challenge stressors could be different over time. For example, a stressor such as workload could lead to some learning consequences in the short-term, as employees learn to work more efficiently. But if the type of work does not change, the learning potential will likely be limited and learning experiences will decline. Studies investigating medium-term processes, such as weekly diary designs could illuminate which short-term effects of stressors vane over time and which effects transition to long-term changes (Baethge et al., 2018; Parker et al., 2021).

Practical implications

In contrast to what would be expected based on the challenge–hindrance stressor framework, our results suggest that practitioners and organisations should avoid challenging employees with high workloads. As workload is strongly positively associated with strain and negatively associated with motivation and learning, it has no benefit for either the organisation or the individual worker. Reducing workload is especially important for care and social workers and for those with very high workloads. In addition, supervisors must regularly communicate with employees to track the workloads their employees are facing. Given recent technological advances, advanced technologies, such as artificial intelligence, decision-aids or robotic systems, may help to reduce employee workload. However, introducing such technologies may have the negative side effect of reducing the complexity and cognitive demands of skilled jobs or introducing a large variation in workload from underload to rapid overload if a system failure occurs. Thus, technological solutions to reduce workload should be thoroughly scrutinised to avoid negative side effects, including reduced cognitive demands (Parker & Grote, 2022; Persson et al., 2001).

The results of the present meta-analysis clearly show that high cognitive demands are associated with learning and motivation. According to action regulation theory, desirable levels of cognitive demands are present when employees are involved in all stages of the task process, including goal development and selection, planning, and task execution, as well as the processing of task-relevant feedback (Frese & Zapf, 1994; Zacher & Frese, 2018). Moreover, work should require different levels of action regulation and thus different levels of cognitive effort. Work tasks should allow workers to use routinised behaviour and well-practiced, automatised behaviour in addition to intentional analysis and problem-solving, as demanded by novel and complex situations (Frese & Zapf, 1994; Ohly et al., 2006, 2017). Such work environments are stimulating, avoid boredom and overload, and provide employees with rich opportunities for learning. However, cognitive demands should also match workers' abilities; otherwise, they have the potential to frustrate and overwhelm workers (Frese & Zapf, 1994).

Limitations

This study has certain limitations. First, most of the studies considered in this meta-analysis had cross-sectional designs, meaning that no conclusions about causality and the directions of effects can be drawn. The positive relations between cognitive demands and learning and motivation could also result from employees with high achievement and learning orientation not only reporting higher levels of motivation but also ending up in jobs with higher job complexity as a result of career success (Dietl et al., 2017). Similarly, high workload is often accompanied by other detrimental working conditions, such as low job control or a difficult social environment (Eurofound, 2017). Such third variables could also explain the negative relationships of workload with motivation and learning. In addition, common method variance could have also introduces biases (Podsakoff et al., 2012). However, sensitivity analyses suggest that the main conclusions drawn from the cross-sectional studies remain unchanged Second, a significant number of studies included in the meta-analysis used self-reported measures for both the predictor and the criterion variable. This may raise additional concerns about common method bias (Podsakoff et al., 2012). We conducted sensitivity analyses to compare studies using self-report measures vs. studies using objective or other-rated measures, but the small numbers of studies did not allow for any subgroup analyses. Thus, future research that uses longitudinal or intervention designs and obtains data from different sources is necessary to draw more robust conclusions about causal effects of workload and cognitive demands on work-related outcomes. Data from different sources could be obtained by using objective ratings for stressors, such as the O*NET classification for job complexity, or by collecting other-reported data from colleagues or supervisors with regard to learning, motivation, and strain.

Third, due to the lack of relevant data in the primary studies, we were unable to examine intervening variables. Specifically, we proposed that (meta-)cognitive and behavioural learning processes are responsible for the differential relationship of cognitive demands and workload with learning. So far, there is a clear lack of studies examining such learning processes, especially in the day-to-day working life where such processes should unfold. We suggest that future research uses diary and experimental study designs to examine mediating variables and capture the underlying processes.

Fourth, most of the relationships between stressors and outcomes showed considerable heterogeneity and our moderator analyses could reduce this heterogeneity only partly. Thus, additional moderator variables that determine whether work stressors are strenuous, motivating, or conducive to learning should be considered in future research. Workers' abilities may play an important moderating role. As has prominently been argued in flow theory (Csikszentmihályi, 1990), a perceived balance between challenges and skills is an important precondition for intrinsic motivation to occur. Therefore, challenges should be motivating as long as they match workers' abilities; however, once they exceed workers' abilities, goal progress will stagnate, and feelings of competence will be thwarted (Bui et al., 2017).

Finally, as the theoretical focus of this study was on challenge stressors, hindrance stressors were not included in the analysis. One may wonder whether not accounting for hindrance stressors might explain differences in the workload-motivation relationship between the present data and the meta-analyses of LePine et al. (2005) and Crawford et al.'s (2010). However, this is unlikely to be the case. In both meta-analyses, the relationship between challenge stressors and motivation did not change substantially after including hindrance stressors. Instead, both the bivariate correlations and the regression coefficients in the model including hindrance stressors were positive for the relationship between challenge stressors and motivation. It is therefore likely that controlling for hindrance stressors would not have substantially changed the workload-motivation relationship in the present meta-analysis.

Conclusion

This meta-analysis tested the relationship of two prominent challenge stressors – workload and cognitive demands – with learning, motivation, and strain. To our knowledge, this study is the first to examine and identify differential associations of workload and cognitive demands with learning. Furthermore, it presented an up-to-date review of the empirical findings regarding the relationships among challenge stressors, motivation, and strain. This study found workload to be negatively related to motivation and learning and positively related to strain. Cognitive demands were positively related to motivation and learning and negatively related to strain. According to these results neither workload nor cognitive demands can be classified as challenge stressors. However, the results underscore the importance of cognitive demands for good work design, as they are motivating and conducive to learning.

Notes

1. We identified only one study on the association between job responsibility and learning.

2. We did not include laboratory studies, as employee samples are more suited to test relationships with informal learning taking place at work than samples of undergraduates who usually participate in laboratory studies. Furthermore, due to the different settings in laboratory and field studies, summarizing both types of studies in a meta-analysis likely increases heterogeneity in the results, rendering the interpretation of the results more difficult.
3. An additional item was available, asking how independently the respondent was able to work. As this item could also refer to coordination demands instead of job control, we decided against using it.Using it as an indicator for job control did not substantially change the results.

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