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The Longitudinal Interaction Effects of Demands and Control on Early Fatigue Indicators

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Abstract

Background: This study investigates short-term lagged relationships between work demands, control and fatigue. A second research question addresses if objectively- and subjectively-measured scores of demands and control converge. Based on the Job-Demand-Control-Support Model, strain and buffer effects are analysed by testing different matching qualities of demand and control variables. Good matches are comprised of work intensity and time latitude. Bad matches are comprised of work complexity and time latitude. **Method**: The method of this study combined observations with adapted survey scales into a three-waves repeated measures design, over the course of 2 months. **Results**: Based on the data of 25 participants, work intensity predicted increased need for recovery and decreased psychological detachment from work and thus supported the strain hypothesis as a central result. The good match of work intensity and time latitude revealed consistent buffering. The bad match of work complexity and time latitude did not exhibit consistent buffering. These interaction effects indicate that matching quality affects buffering a second central result. Furthermore, work complexity showed effects not aligned with the strain hypothesis and indicated a reducing main effect on need for recovery which requires additional discussion and investigation. The comparison of objective and subjective scores revealed high overall convergence which differed between the factors work intensity, work complexity time latitude. This third central result showed that the convergence of objective and subjective scores differs between the kind of working condition that is measured. **Discussion**: The findings are discussed regarding prior research, directions of effects and mechanisms of action. While comparisons are limited due to differences in research designs and sample sizes, this study adds to the insights on buffering effects and extends the matching-principle. It also adds to the body of research about short-term strain effects and makes an attempt at testing convergence between objective and subjective scores of working conditions. Implications for future research are given in an attempt to progress the current findings and their meaning for practitioners is highlighted.

Keywords

Job-Demand-Control-Support Model, Strain Hypothesis, Buffer Hypothesis, Need for Recovery, Psychological Detachment from Work

1. Introduction

The topic of straining work environments has been subjected to a long history of research (Bliese et al., 2017). Concurrently, given the rising importance of work flexibility and socially responsible practices among employers for Generation Z (Agarwal & Vaghela, 2018), alongside the need for retention of older employees (Lichtenthaler & Fischbach, 2016), advancements in healthy job design are nowadays more important than ever before. This study takes a "shortitudinal" (defined as a longitudinal design with a short time span) (Dormann & Griffin, 2015: p. 1) approach to progress the research on seminal frameworks in organisational health psychology, the Job-Demand-Control-Support Model (Johnson & Hall, 1988; Karasek, 1979) and the Job-Demand-Resources Model (Bakker & Demerouti, 2007), focusing on short-term lagged effects. This study aims to contribute to the theory and practice of job design, by addressing common challenges when measuring working conditions through surveys (Lesener et al., 2019) and advancing the principle of matching demands and control (Cohen & Wills, 1985; Jonge & Dormann, 2003).

2. Literature Review

Research Gaps Regarding of Work Strain Studies

The *Job-Demand-Control Model* (JDC) (Karasek, 1979) defines job demands and job control, and explains main and interactive effects on strain. The term job demands refers to sources of stress within the work environment, while job control is defined as decision latitude (Karasek, 1979). The model also explains job strain and suggests that it occurs in jobs jobs, which impose high demands and low control. The model was updated to the Job-Demand-Control-Support Model (JDCS) by Johnson & Hall (1988), who added social support as a third dimension. The present study refers to the model as JDCS (Johnson & Hall, 1988), as it expands Karasek's (1979) original concept. Scholars categorised challenge and hindrance demands (Podsakoff et al., 2007), yet a distinction can be challenged, if a stressor's nature is defined based on individual appraisal (Lazarus & Folkman, 1984). Although not explicitly defined in Karasek's (1979) work, scholars formulated hypotheses pertaining to the impact of demand and control on health (Häusser et al., 2010). The *strain hypothesis* (van Vegchel et al., 2005) predicts increased strain due to high demands and predicts control to anticipate decreased strain. Similarly, the iso-strain hypothesis (Johnson & Hall, 1988) predicts the highest strain when demands are high, control is low, and support is low. The *buffer hypothesis* refers to an interaction of demands and control (Van der Doef & Maes, 1999). It predicts effects by high demands to be buffered by high control, causing active and learning-inducing work (Van der Doef & Maes, 1999). Bakker & Demerouti (2007) criticised the model's static nature and lack of attention to motivational processes and justified the more flexible Job-Demands-Resources model (JD-R). It suggests the influence of control factors to differ between jobs, and that factors should be broadly defined as job resources. In line with previous JDCS research that deployed diverse measures for working conditions (Fila et al., 2013), the present study defines demands, control, and support as categories, not specific constructs. The present study still refers more to the JDCS than JD-R because it does not address motivation. Due to the high similarity of the models describing strain, both JDCS and JD-R research is relevant for the issues under investigation.

Empirical support for the JDCS is mixed and requires a nuanced consideration. Vote-counting reviews on the (iso-) strain hypothesis conclude that additive effects on wellbeing are supported by most studies (de Lange et al., 2003; Häusser et al., 2010; Van der Doef & Maes, 1999). Häusser et al. (2010) demonstrate that all studies with $N > 3000$ show full support. Findings were more consistent for demand and control (JDC) than for demand, control and support (JDCS), which is attributed to a stochastic effect of including another predictor. A meta-analysis by Fila et al. (2013), analysing main effects confirmed moderate cross-sectional correlations between emotional exhaustion (Maslach, 1998) and demands, control, and support. As support was higher cross-sectionally than in the few longitudinal designs, scholars call for more longitudinal studies (Häusser et al., 2010; Van der Doef & Maes, 1999). The recent meta-analysis by Lesener et al. (2019) confirmed longitudinal main effects on emotional exhaustion, but also criticised the scarcity of longitudinal research, a limitation the present study strives to address.

Regarding the buffer hypothesis, empirical support is weaker (de Lange et al., 2003; Fila, 2016; Fila et al., 2013; Häusser et al., 2010; Van der Doef & Maes, 1999). De Lange et al. (2003) concluded that stronger studies which regarded design, time lags (meant as the time between two measurement points), measurement, analysis and non-response examination, did not demonstrate more significant effects than weaker studies. Accordingly, only 6% of reviewed studies by Häusser et al. (2010) were fully supportive of interactive effects. Significant findings were particularly few in longitudinal studies (Häusser et al., 2010; Van der Doef & Maes, 1999), able to test causal effects (Kain & Jex, 2010). Despite the limitations of vote-counting reviews regarding skewing and near-significance (Hunter & Schmidt, 2004, as cited in Fila et al., 2013), research shows only limited support for buffering. The *matching principle* (Cohen & Wills, 1985), referring to how measures of demands, control, or support match, has been discussed as a reason why buffer effects cannot be consistently demonstrated (de Lange et al., 2003; Häusser et al., 2010; Van der Doef & Maes, 1999). A good match means demands, and control are linked to the same capacity such as workload and timing control; a bad match implies that they are linked to different capacities like emotional demands and timing control (Fila, 2016). Studies which matched variables well, detected twice as many significant buffer effects than studies that did not match well (Häusser et al., 2010). Matching was extended to triple-matching (Jonge & Dormann, 2003), meaning strains should also be matched with demands and control. It appeared that this could lead to more significant effects than if only demands and control match (Chrisopoulos et al., 2010; de Jonge & Dormann, 2006). These studies however classified demands, control/resources, and strains broadly as cognitive, emotional, or physical (Chrisopoulos et al., 2010; de Jonge & Dormann, 2006) and such simplicity could be questioned. Firstly, tasks may require workers to engage in both cognitive processing and physical actions. Secondly, a control factor like time latitude (Sonntag & Feldmann, 2022) could be leveraged to buffer either a cognitive, physical, or emotional demand. Finally, time latitude could buffer some, but not all, cognitive demands. If the demand is a high load of cognitive tasks, autonomously controlling one's work time may serve as a buffer, since the individual can allocate specific time slots for different tasks, prioritise tasks and situationally work faster or slower. Yet, if the cognitive demand involves processing complex information (Sonntag & Feldmann, 2022), it seems logical that merely increasing time latitude may not yield a buffering effect. Simply put, when people have to process complex information, the ability to control work time does not significantly benefit them, when complexity exceeds analytic capabilities.

The present study proposes that matching is more context-dependent, and attempts testing the matching of demands and control based on if a compelling argument can be made, that control can buffer the demand because it is complementary to the demand. Besides testing the strain hypothesis longitudinally, the present study therefore aims to test the buffer hypothesis by examining the research question of how matching quality affects buffering.

Hypothesis 1 (a): Demands positively predict later fatigue (strain hypothesis).

Hypothesis 1 (b): Control negatively predicts later fatigue (strain hypothesis).

Hypothesis 2 (a): The interaction of demands and control predicts later fatigue if demands and control are matched appropriately (buffer hypothesis).

Hypothesis 2 (b): The interaction of demands and control does not predict later fatigue if demands and control are not matched appropriately (buffer hypothesis).

Beyond the matter of matching, the topic of appropriate time lags for longitudinal work strain studies received little coverage. De Lange et al. (2003) rated a time lag of over 1 year as more appropriate, even if shorter lags are grounded in theory. Lesener et al. (2019) disregarded lag length and emphasised the theoretical argument and the number of waves, with more waves yielding higher validity. Reviewed longitudinal studies by Lesener et al. (2019) had mean lags of 11 months, whilst few studies, such as Huang et al. (2011), used much shorter lags, and mainly measured emotional exhaustion through the Maslach Burnout Inventory (Maslach et al., 1997) or Oldenburg Burnout Inventory (Halbesleben & Demerouti, 2005). This explains long-term effects, yet for early prevention it is required to also understand short-term work-fatigue relationships, which is the goal of the present study.

Need for recovery, defined as the need to replenish energy levels as a work consequence and an early fatigue symptom (Veldhoven, 2008), predicts later emotional exhaustion (Simbula et al., 2019). In past research, it showed to be correlated positively with demands and negatively with control (Jansen, 2003; Machin & Hoare, 2008; Sonnentag & Zijlstra, 2006). De Raeve et al. (2007) tested a 4-month time lag and demonstrated how changes in demands predicted increased need for recovery; changes in control showed decreasing effects of need for recovery. Increased need for recovery through demands is explained by loss spirals, if work demands deplete resources beyond what a person can conserve (Holmgreen et al., 2017). Effects by De Raeve et al. (2007) were however small and insignificant, when controlling for other confounding factors. Moreover, buffer effects were not tested, which necessitates further research on recovery.

A lack of *psychological detachment from work*, defined as not leaving one's work psychologically behind (Sonnentag & Fritz, 2007), is another early fatigue-related factor. It has been described as a predictor of emotional exhaustion (Demerouti et al., 2012), is predicted by demands on a day level (Sonnentag & Bayer, 2005) correlates positively with control (Ward & Steptoe-Warren, 2013). It furthermore mediated the relationship between working availability and emotional exhaustion in a study using 2-month time lags (Dettmers, 2017). This is explained by the stressor-detachment model (Sonnentag & Fritz, 2015). It proposes that job stressors inhibit psychological detachment through negative activation, and that lack of detachment mediates strain reactions and moderates the main effects of demands. Since the outlined fatigue indicators, which are relevant for long-term exhaustion have up to this point been researched either on a day level, or with lags of several months, the present study "shortitudinally" (Dormann & Griffin, 2015: p. 1) closes the gap. Using time lags of several weeks, it imposes a second research question; do the strain and buffer hypothesis apply to the fatigue indicators psychological detachment from work and need for recovery?

A limitation of most work strain studies is a reliance on self-report measures (Lesener et al., 2019). Even though this seems reasonable for research economics, particularly in longitudinal designs, this imposes issues. Measuring objective working conditions with subjective measures is conceptually incongruent (van Vegchel et al., 2005) and cannot be fully valid, as individuals perceive stressors through their individual appraisal (Lazarus & Folkman, 1984). Since stress appraisal is described as a process, perceived stressors can be expected to differ between individuals, and it depends on when it was measured during the appraisal process (Lazarus & Folkman, 1984). Bias through monomethods (Spector, 2006) can further inflate correlations through social desirability (Chen et al., 1997) or negative affectivity (Watson et al., 1987). In contrast, the issue of common method variance has been discussed as overstated (Spector, 2006), which raises the question of whether objective measures are required. Convergence between objective and subjective scores of working conditions has been tested previously, by checking correlations among objective scores of ward organisation and nurse-rated scores of comparable factors (Stab et al., 2016). The authors found correlations to be generally positive, though only two were statistically significant. When convergence was high, around 25% of variance of the subjective score could be explained by the objective score, and vice versa. They partly attributed their effects to observation and self-report contents being comparable but not identical, thus measuring different parts of the same dimension, limiting convergence (Stab et al., 2016). The same argument can also be applied to findings by Melamed et al. (1995) which showed moderate correlations between subjective monotony scores and different objective assessments of monotony, where the explained variance was, on average, close to 8%. Further research is therefore required to test convergence under the condition of highly identical objective and subjective measures, and, ideally, to test how both predict strain. Generating objective workplace data to predict strain exceeds this study's resources, as it requires onsite observations by experts in 30 units with three individuals each (van Dick et al., 2005). Instead, the present study aims to generate objective workplace data in a small scope and to validate scores by addressing a third research question; do subjective and objective scores of demands and control converge? Accordingly, additional hypotheses follow:

H3 (a): Subjective and objective demand scores converge (convergence hypothesis).

H3 (b): Subjective and objective control scores converge (convergence hypothesis).

Convergence decreases if respondents are strongly biased, therefore the convergence hypotheses suggest insignificant differences between subjective and objective scores. Such comparisons cannot resolve the outlined conceptual issue, but convergence between subjective and objective scores can validate the subjective measurements to an extent.

3. Method

3.1. Sample

The sample consists of 25 workers of either a subject service team (n = 11), nutrition team (n = 7) or coordination team (n = 7) during a 2-month project. The total size of all three teams combined was of 41, which signifies a return rate of 61%, the dropout rate was 26%. Workers from subject service and nutrition teams were working students with backgrounds in medicine and nutritional science. Asides from team membership, no demographic information was surveyed, for data protection purposes. The demographic characteristics of sample can therefore not be precisely described. Yet it can be stated, that majority of the team members were female and between the age of 25 and 40 years old. It can also be assumed, that the coordination team members were older than the members of the nutrition and subject service teams.

3.2. Design and Procedure

The study deployed a three-wave repeated measures design, combining direct non-participating (Ciesielska et al., 2018) onsite observations with online surveys. To retrieve objective and subjective data, workplaces were observed by an expert and rated by surveyed workers. Subjective scores were measured for predicting strain and testing them against the objective scores. Separate observations were conducted for the teams subject service and nutrition. Coordination workers were surveyed, but not included in the observation, for research-economic reasons. For measuring fatigue indicators, only survey data was collected. The data was collected between May 1st and July 4th of 2023. The present study was designed around a 2-month research project in Germany. While said project cannot be disclosed in detail, it consisted of three study phases. Phase one had a duration of 15 days, phase two of 30 days and phase three had a duration of 14 days. The study workers (the subjects of the current sample) carried out different tasks throughout these phases. These changes in tasks applied to the subject service team most prominently, and to a lesser degree to the nutrition and coordination team. Working conditions of the study workers were observed once during each phase, and study workers were concurrently surveyed online during three time frames. Onsite observations were conducted by a trained observer with a bachelor's degree in Industrial and Organisational Psychology. For team subject service, each observation took 6 hours, covering morning, afternoon, and night shifts. For team nutrition, each observation took 4 hours, covering morning and afternoon shifts. The observer did not know in advance, which workers were on site on observation days, and participants were not involved in scheduling. Survey participation was voluntary, surveys were sent out several days after a phase had started, setting time lags of 16 days between measurements. Surveys were conducted over three 7-day periods, to which workers had access during work or leisure time. This gave adequate time to experience working conditions and kept surveys accessible long enough to increase response rates.

3.3. Observation Measures

Working conditions. Demands and control were observed using the Gefährdungsbeurteilung Psychischer Belastung (GPB) (Sonntag & Feldmann, 2022). This is an objective observation instrument, covering 13 dimensions of demands and resources, based on the JDC(S) (Johnson & Hall, 1988; Karasek, 1979). Objectivity, reliability and validity regarding content, construct and criterion validity were found to be satisfactory in various industries (Feldmann, 2018). Dimensions consist of four items each, rated on a fully labelled 5-point scale (almost never - rarely - sometimes - frequently - constantly). Traditionally, the instrument is deployed by multiple observers, who make independent and individual ratings first. Afterwards scores are determined through consensus finding in a second step.

3.4. Survey Measures

Working conditions. The dimensions work complexity (demand), work intensity (demand) and time latitude (control) were included, using adapted items from the GPB (Sonntag & Feldmann, 2022). This entailed formulating questions into statements and wording them in first person. An example is *Can the employee himself determine when he performs the individual steps in his work*? (time latitude observation), was changed to *I can determine myself when I perform the individual steps in my work* (time latitude survey). No changes were made to the answering scale. The adaption to a survey format kept content identical between observer and survey scores, and was more appropriate than choosing a different scale, as harmonising the measures this way maximised comparability between the objective and subjective scores. The factors work complexity, work intensity and time latitude were chosen for the survey, to test the matching principle. The argument is that work intensity and time latitude are a good match, while work complexity and time latitude are not. Work intensity (sample item: *Time pressure can arise in my work* (*especially due to unplanned events*)) refers to a quantitative demand of how much work a person needs to handle within a time frame (Sonntag & Feldmann, 2022) and time latitude gives that person autonomy over the time-management regarding said work. Thus, these variables match well because both are connected to the capacity of time. Contrarily, work complexity (sample item: *As part of my job*, *I work on tasks where I have to absorb and process a lot of different or very complex information*) refers to the complexity of information processing required through one's work (Sonntag & Feldmann, 2022), which, as described in the theory part, should be buffered to a lesser degree by time latitude.

Fatigue variables. The German psychological detachment from work scale (Sonnentag & Fritz, 2007) was used as a job-related fatigue indicator. It is a four-item measure, rated on a 5-point scale ranging from 1 (I do not agree at all) to 5 (I fully agree). A sample item is*: In my free time I forget about work.* Also, a German version (derived through back-and-forth-translation) of the need for recovery scale (Veldhoven, 2008) was administered in short form as done by Stevens et al. (2019) to measure job-related fatigue. The three-item measure was rated on a dichotomous scale, ranging from 1 (yes) and 2 (no). A sample item is: *Generally*, *I need more than an hour before I feel completely recuperated after work*.

Control variables. No control variables were measured to keep the questionnaire as short as possible, this was deemed acceptable to minimise participants dropping out of the study.

3.5. Psychometrics

Internal consistencies at each time frame are displayed in **Table 1**. After assessing internal consistencies, the first item of the time latitude scale was removed, which resulted in increased reliability of above $\alpha = 0.70$. This was based on item-whole correlation (**Table 2**). The reduced version was used for all subsequent analyses. Work intensity, work complexity and psychological detachment showed satisfactory internal consistencies above α = 0.70. Need for recovery missed this criterion and alphas ranged from 0.550 to 0.613. Test-retest correlations (Table 3) for all work variables and psychological detachment showed generally satisfactory stabilities. Need for recovery showed lower stabilities ranging from 0.415 to 0.514.

Table 1. Internal consistencies.

	Number of items	Cronbach's α		
		T1	T2	T3
Time latitude	4	0.657	0.599	0.686
Time latitude (modified)	3	0.839	0.727	0.792
Work intensity	4	0.870	0.738	0.924
Work complexity	4	0.839	0.711	0.798
Psychological detachment	4	0.921	0.849	0.874
Need for recovery	3	0.550	0.599	0.613

Table 2. Item analysis for time latitude.

	Item-rest correlation T1	Item-rest correlation T2	Item-rest correlation T3
Item 1	0.168	0.172	0.251
Item 2	0.524	0.670	0.482
Item 3	0.609	0.309	0.694
Item 4	0.653	0.501	0.552

Item 1: Ich kann die Dauer und/oder Lage der täglichen Arbeitszeit selbst bestimmen. Item 2: Ich kann bei meiner Tätigkeit selbst festlegen, wann ich die einzelnen Arbeitsschritte ausführe. Item 3: Ich kann bei Zeitdruck die Bearbeitungsabfolge ändern, bzw. den Arbeitsauftrag variieren, um mich zu entlasten. Item 4: Ich kann im Rahmen meiner Tätigkeit die Arbeitsgeschwindigkeit selbst bestimmen.

Table 3. Pearson correlations of survey variables.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Work intensity (T1)	-															
2	Work intensity (T2)	0.752**	-														
3	Work intensity (T3)	0.833**	0.655**	-													
4	Work complexity (T1)	0.825**	0.691**	0.679**	-												
5	Work complexity (T2)	0.671**	0.649**	0.596**	0.800**	-											
6	Work complexity (T3)	0.746**	0.494*	0.748**	0.749**	0.798**	-										
7	Time latitude (T1)	−0.308	−0.265	−0.376†	−0.235	−0.157	−0.365†	-									
8	Time latitude (T2)	−0.425*	−0.411*	−0.312	−0.216	−0.170	−0.116	0.634**	-								
9	Time latitude (T3)	−0.216	−0.210	−0.397*	−0.105	0.011	−0.191	0.784**	0.515**	-							
10	Need for recovery (T1)	0.076	0.156	0.035	−0.086	0.096	−0.064	−0.161	−0.159	−0.221	-						

Continued

11	Need for recovery (T2)	−0.064	0.255	−0.005	−0.058	−0.026	−0.245	−0.151	−0.307	−0.327	0.514**	-					
12	Need for recovery (T3)	0.357†	0.342†	0.419*	0.339†	0.190	0.211	−0.402*	−0.301	−0.480*	0.415*	0.426*	-				
13	Psychological detachment (T1)	−0.246	−0.330	−0.104	−0.442*	−0.395†	−0.183	−0.019	−0.039	−0.042	−0.247	−0.144	−0.324	-			
14	Psychological detachment (T2)	−0.440*	−0.569**	−0.282	−0.471*	−0.472*	−0.251	0.002	0.198	−0.051	−0.084	−0.151	−0.100	0.692**	-		
15	Psychological detachment (T3)	−0.410*	−0.547**	−0.329	−0.535**	−0.454*	−0.303	0.235	0.237	0.130	−0.219	−0.290	−0.311	0.687**	0.752**	-	
16	Team	0.763**	0.514**	0.690**	0.809**	0.680**	0.828**	−0.345†	−0.259	−0.238	−0.142	−0.120	0.163	−0.313	−0.346†	−0.395†	-

Note. N = 25 df = 23. † $p < 0.1$ * $p < 0.05$ ** $p < 0.01$.

3.6. Statistical Analysis

Descriptive and inferential analyses were conducted using SPSS 29 (IBM Corp, 2022) and Jamovi (JAMOVI, 2022). Observation scores were calculated with Excel (Microsoft, 2019). Inclusion criteria was that participants responded to all three surveys. No cases were excluded. To assess potential attrition bias, means for working conditions and fatigue indicators were compared between dropped out (n = 9) and complete cases (n = 25) in a robust Welch's ANOVA. No significant differences were detected (**Table 29**). Hypothesis 1 (a/b) and Hypothesis 2 (a/b) were tested in two hierarchical multiple regression analyses, predicting need for recovery and psychological detachment. Hypothesis 3 (a/b) was tested with one sample t-tests. The subjective means for work intensity, work complexity and time latitude were compared to the objective scores for each time frame. T-tests were conducted in such a way that the subjective scores were tested against the objective scores and entered as test values. Comparisons were done separately for the teams subject service and nutrition as these were separate workplaces. Hedge's correction g was used to interpret the standardised effect sizes to accommodate the small subsample sizes of n = 11 (subject service) and n = 7 (nutrition). Because of the low power of the Shapiro-Wilk-test at such sample sizes, distributions were visually assessed and found to be non-normal. Thus, 1000 random sample-bootstrapping, and the bias corrected and accelerated method were used.

4. Results

Pearson correlations and descriptives are displayed in **Tables 3-5**. Need for recovery (T3) showed several positive moderate correlations with work intensity and work complexity at all three time frames. With time latitude at all three time frames, small to moderate negative correlations were found. Psychological detachment (T2) and (T3) showed moderate positive correlations with work intensity and work complexity at all three time frames. No substantial correlations were found with time latitude. Not all moderate effects were significant at a 5% (α = 0.05) level. The variable team was further moderately correlated with psychological detachment at all three time frames.

Table 4. Descriptives of survey variables.

	N	Mean	SD	Min	Max
Work intensity T1	25	2.620	1.059	1.000	4.000
Work intensity T2	25	2.900	0.677	2.000	4.250
Work intensity T3	25	2.210	0.912	1.000	3.750
Work complexity T1	25	2.790	0.978	1.250	4.750
Work complexity T2	25	2.920	0.770	1.750	4.250
Work complexity T3	25	2.490	0.885	1.000	3.750
Time latitude T1	25	3.050	0.860	1.500	4.500
Time latitude T2	25	2.890	0.613	1.750	3.750
Time latitude T3	25	3.260	0.738	2.000	4.750
Psychological detachment T1	25	3.580	0.929	1.000	5.000
Psychological detachment T2	25	3.510	0.808	1.500	4.750
Psychological detachment T3	25	3.660	0.819	1.750	4.750
Need for recovery T1	25	1.507	0.335	1.000	2.000
Need for recovery T2	25	1.627	0.338	1.000	2.000
Need for recovery T3	25	1.467	0.360	1.000	2.000

Table 5. Partial correlations of work intensity and work complexity.

Control variables				1	2	3	4	5	6
Team	1	Work intensity T1	Correlation	-					
			p	.					
	2	Work intensity T2	Correlation	0.648***	-				
			p	<0.001	.				
	3	Work intensity T3	Correlation	0.656***	0.485*	-			
			p	<0.001	0.016	.			
	4	Work complexity T1	Correlation	0.547**	0.545**	0.284	-		
			p	0.006	0.006	0.178	.		
	5	Work complexity T2	Correlation	0.321	0.476*	0.240	0.580**	-	
			p	0.126	0.019	0.259	0.003	.	
	6	Work complexity T3	Correlation	0.316	0.142	0.435*	0.241	0.571**	-
			p	0.132	0.509	0.034	0.258	0.004	.

Note. N = 25. df = 22. * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

4.1. Strain and Buffer Hypothesis

To test main effects of work intensity, work complexity, and time latitude on need for recovery and psychological detachment, two separate two-step multiple hierarchical regression models were conducted. Model A predicted need for recovery (T3). In the first step, the independent (T1) variables: baseline need for recovery, work intensity, work complexity, time latitude and interactions were included. Assumption tests showed no violation of the assumption of normally distributed residuals (W = 0.920, $p > 0.05$), no multicollinearity (values of variance inflation factor < 10 and tolerance > 0.1) and no autocorrelation (Durbin-Watson statistic = 2.54). No maximum values for Cook's distance exceeded the threshold of 1, indicating that no influential cases diminished the accuracy of the prediction (Cook & Weisberg, 1982). A graphical analysis of the residuals further indicated homoscedasticity. The step one model was significant $p \le 0.05$, explaining 43,1% of adjusted variance. Work intensity (T1) showed a significant increasing effect on need for recovery (T3) b = 1.050, [0.223, 1.877] 95% CI, t = 2.666, β = 3.086, p = 0.016. Work complexity (T1) did not show a significant effect according to the $p < 0.05$ criterion, but it predicted decreased need for recovery on a 10% (α = 0.1) level b = −0.868, [−1.906, 0.171] 95% CI, t = −1.756, β = −2.357, p = 0.096. The direction of this effect is reversed, compared to the positive bivariate correlation between work complexity (T1) and need for recovery (T3) (**Table 6**). The interaction term of work intensity (T1) and time latitude (T1) significantly predicted need for recovery (T3) b = −0.339, [−0.591, −0.087] 95% CI, t = −2.826, β = −3.234, p = 0.011. The negative interaction effect implies that an increase in one variable makes the main effect of the other variable more negative. The interaction term of work complexity (T1) and time latitude (T1) also significantly predicted need for recovery b = 0.308, [0.005, 0.610] 95% CI t = 2.135, p = 0.047. This positive interaction effect implies that an increase in one variable makes the main effect of the variable more positive. It is noteworthy, that the standardised beta coefficients exceeded 1, when entering work intensity, work complexity, time latitude and the interaction terms in Step one. As work intensity showed a positive effect on need for recovery, and work complexity showed negative effect, possible suppression occurred, as work intensity and work complexity themselves were shown to be positively correlated (**Table 3**).

Table 6. Two-step regression on need for recovery (Model A).

Variable	B	SE	p	95% CI	β	R^2	ΔR^2
Step 1						0.574	
Intercept	0.882	0.767	0.265	[−0.730, 2.494]			
Need for recovery T1	0.372*	0.175	0.048	[0.005, 0.740]	0.347		
Work intensity T1	1.050*	0.394	0.016	[0.223, 1.877]	3.086		
Work complexity T1	−0.868†	0.494	0.096	[−1.906, 0.171]	−2.357		
Time latitude T1	−0.077	0.196	0.700	[−0.489, 0.336]	−0.198		
T1 → work intensity * time latitude	−0.340*	0.120	0.011	[−0.591, −0.087]	−3.234		
T1 → work complexity * time latitude	0.308*	0.144	0.047	[0.005, 0.610]	3.061		

Continued

Step 2						0.700	0.127
Intercept	3.588	2.236	0.134	[−1.283, 8.460]			
Need for recovery T1	0.176	0.252	0.499	[−0.373, 0.724]	0.163		
Work intensity T1	1.291*	0.526	0.030	[0.144, 2.437]	3.795		
Work complexity T1	−0.920	0.622	0.165	[−2.275, 0.435]	−2.499		
Time latitude T1	−0.023	0.218	0.918	[−0.497, 0.4511]	−0.0593		
T1 → work intensity * time latitude	−0.365*	0.148	0.030	[−0.688, −0.042]	−3.484		
T1 → work complexity * time latitude	0.308	0.174	0.102	[−0.071, 0.688]	3.069		
Need for recovery T2	0.447	0.270	0.124	[−0.142, 1.036]	0.419		
Work intensity T2	−1.004	0.924	0.299	[−3.018, 1.001]	−1.888		
Work complexity T2	−0.251	0.549	0.656	[−1.447, 0.945]	−0.536		
Time latitude T2	−1.006	0.697	0.175	[−2.525, 0.514]	−1.860		
T2 → work intensity * time latitude	0.279	0.275	0.331	[−0.320, 0.878]	1.758		
T2 → work complexity * time latitude	0.080	0.170	0.647	[−0.291, 0.450]	0.623		

Note. N = 25. df = 18 for step 1. df = 2 for step 2. † $p < 0.1$ * $p < 0.05$.

In step two, (T2) need for recovery, work intensity, work complexity, time latitude, and the interaction terms were included. Adding the predictors in step two did not violate the assumption of normally distributed residuals (W = 0.980, $p >$ 0.05). Furthermore, no multicollinearity (values of variance inflation factor < 10 and tolerance > 0.1) and no autocorrelation (Durbin-Watson statistic = 1.59) or heteroscedasticity were present. No maximum values for Cook's distance exceeded the threshold of 1, indicating that no influential cases diminished accuracy of the prediction (Cook & Weisberg, 1982). The step two model was significant only on a 10% (α = 0.1) level, explaining 40.1% of adjusted variance. Work intensity (T1) still showed a significant increasing effect on need for recovery (T3) b = 1.291, [0.144, 2.437] 95% CI, t = 2.453, β = 3.795, $p = 0.030$. The effect of the interaction term (T1) of work intensity and time latitude on need for recovery also remained significant b = −0.365, [−0.688, −0.042] 95% CI, t = −2.462, $p = 0.030$. Work complexity (T1) and its interaction (T1) with time latitude no longer demonstrated any significant effects (**Table 6**). None of the (T2) variables showed a significant effect on need for recovery (T3) (**Table 6**). In both step one and step two, the coefficients of prior need for recovery indicated moderate stability (**Table 6**).

Model B predicted (T3) psychological detachment and was conducted analogously to Model A, including the (T1) working conditions and interaction terms in step one, and the (T2) working conditions and interaction terms in step two. The difference was that in step one, baseline (T1) psychological detachment was controlled for and in step two, (T2) psychological detachment was included. Need for recovery was not included in Model B, as it predicted a different outcome variable. Model B also controlled for the variable team, as it showed near significant correlations with psychological detachment (Table 3). Assumption tests showed no violation of the assumption of normally distributed residuals (W = 0.980, $p > 0.05$), no multicollinearity (values of variance inflation factor < 10 and tolerance > 0.1) and no autocorrelation (Durbin-Watson statistic = 1.53). No maximum values for Cook's distance exceeded the threshold of 1. A graphical analysis of the residuals further indicated homoscedasticity. The step one model was significant $p \leq 0.05$, explaining 41,3% of adjusted variance. In step one, none of the time one working conditions or interaction terms showed significant effects on time three psychological detachment (Table 7).

Table 7. Two-step regression on psychological detachment from work (Model B).

Variable	B	SE	*p*	95% CI	β	R^2	ΔR^2
Step 1						0.584	
Intercept	2.200	1.800	0.238	[−1.599, 5.998]			
Psychological detachment T1	0.526*	0.159	0.004	[0.190, 0.862]	0.597		
Work intensity T1	−0.216	1.086	0.845	[−2.508, 2.075]	−0.279		
Work complexity T1	−0.251	1.497	0.869	[−3.409, 2.907]	−0.300		
Time latitude T1	0.043	0.457	0.926	[−0.922, 1.008]	0.049		
T1 → work intensity * time latitude	0.052	0.350	0.883	[−0.685, 0.790]	0.219		
T1 → work complexity * time latitude	0.006	0.414	0.988	[−0.866, 0.879]	0.028		
Team	0.124	0.351	0.728	[0.617, 0.866]	0.129		
Step 2						0.801	0.217
Intercept	9.589†	5.127	0.088	[−1.695, 20.874]			
Psychological detachment T1	0.362	0.202	0.101	[−0.084, 0.808]	0.411		
Work intensity T1	1.427	1.260	0.282	[−1.347, 4.201]	1.843		
Work complexity T1	−1.512	1.713	0.396	[−5.282, 2.258]	−1.805		
Time latitude T1	0.268	0.446	0.560	[−0.714, 1.251]	0.304		
T1 → work intensity * time latitude	−0.392	0.404	0.352	[−1.280, 0.496]	−1.643		
T1 → work complexity * time latitude	0.341	0.477	0.490	[−0.709, 1.390]	1.490		
Team	0.320	0.370	0.406	[−0.494, 1.134]	0.332		
Psychological detachment T2	0.354	0.254	0.191	[−0.205, 0.914]	0.349		
Work intensity T2	−4.219*	1.881	0.047	[−8.359, −0.088]	−3.486		
Work complexity T2	1.331	1.064	0.237	[−1.010, 3.673]	1.251		
Time latitude T2	−2.772†	1.467	0.085	[−6.002, 0.457]	−2.253		
T2 → work intensity * time latitude	1.266†	0.577	0.051	[−0.004, 2.536]	3.510		
T2 → work complexity * time latitude	−0.384	0.340	0.283	[−1.134, 0.365]	−1.320		

Note. N = 25. df = 17 for step 1. df = 1 for step 2. † $p < 0.1$ * $p < 0.05$.

After adding the (T2) working conditions and interaction terms, and controlling for (T2) psychological detachment, residuals were still found to be normally distributed ($W = 0.976$, $p > 0.05$), no multicollinearity (values of variance inflation factor < 10 and tolerance > 0.1), or autocorrelation (Durbin-Watson statistic = 1.61) was detected. No maximum values for Cook's distance exceeded the threshold of 1. The step two model was significant $p \leq 0.05$, explaining 56.6% of adjusted variance. Work complexity (T2) and the interaction (T2) of work complexity and time latitude showed no significant effects on psychological detachment (T3) (**Table 7**). Work intensity (T2) predicted significantly decreased psychological detachment $b = -4.219$, [− 8.359, −0.088] 95% CI, $t = -2.242$, $\beta = -3.486$, $p = 0.047$. On a 10% ($\alpha = 0.1$) level, time latitude (T2) also predicted significantly decreased (T3) psychological detachment $b = -2.772$, [− 6.002, 0.457] 95% CI, $t = -1.890$, $\beta = -2.253$, $p = 0.085$. The direction of this effect is reversed compared to the positive bivariate correlation between time latitude (T2) and psychological detachment (T3). The interaction (T2) of work intensity and time latitude showed a near significant positive effect $b = 1.266$, [−0.004, 2.536] 95% CI, $t = 2.194$, $\beta = 3.510$, $p = 0.051$. This positive effect implies that an increase in one variable makes the main effect of the other variable more positive. The standardised beta coefficients exceeded 1 in this model, as was the case for Model A, indicating suppression effects. Stabilities indicated by the coefficients of prior psychological detachment were found to be moderate, in both step one and step two (**Table 7**).

4.2. Convergence Hypothesis

For the sake of brevity, only the central findings are summarised below. The descriptive statistics of the objective scores of working conditions are displayed in **Table 8** for the subject service team and in **Table 9** for the nutrition team. The results of all 18 comparisons are displayed in the Appendix (**Tables 10-27**). The average standardised effect size of all comparisons was $g = 0.631$ and can be described as moderate. The pattern of results indicates that objective and subjective scores did not differ significantly in most comparisons: 12 out of 18 comparisons (66.67%) detected no significant differences between subjectively measured scores of demands and control and objective observation scores. One test (5.56%) detected near significant differences on a 10% ($\alpha = 0.1$) level, and five tests (27.78%) detected significant differences on a 5% ($\alpha = 0.05$) level. On average, objective and subjective scores differed by 10.48%, work complexity scores showed the lowest percent differences (5.56%), followed by work intensity (10,38%) and time latitude (15.49%). The most significant differences between objective and subjective scores were found in the variable time latitude, followed by work intensity. The differences in objective and subjective scores for time latitude were found to be significant at the 5% ($\alpha = 0.05$) level in three instances, and nearly significant at the 10% ($\alpha = 0.1$) level in one instance. For work intensity, significant differences at the 5% level were found in two instances. There was no clear pattern regarding the direction of differences between objective and subjective scores, objective scores were found to be larger or smaller than subjective scores in nine instances each.

Table 8. Descriptives of working conditions for subject service.

	Subject service subjective Mean	Subject service objective workplace-level score	% Difference between subjective and objective score
Work intensity T1	1.568	1.750	11.465
Work intensity T2	2.431	2.50	2.881
Work intensity T3	1.386	1.750	25.899
Work complexity T1	1.931	1.750	9.326
Work complexity T2	2.341	2.250	3.846
Work complexity T3	1.681	1.750	4.167
Time latitude T1	3.205	2.750	14.063
Time latitude T2	3.068	2.750	10.423
Time latitude T3	3.455	2.750	20.290

Table 9. Descriptives of working conditions for nutrition.

	Nutrition subjective Mean	Nutrition objective workplace-level score	% Difference between subjective and objective score
Work intensity T1	3.571	3.250	8.964
Work intensity T2	3.357	3.250	3.274
Work intensity T3	2.964	3.250	9.797
Work complexity T1	3.178	3.000	5.660
Work complexity T2	3.214	3.000	6.542
Work complexity T3	2.892	3.000	3.806
Time latitude T1	2.821	3.250	15.248
Time latitude T2	2.642	3.250	23.106
Time latitude T3	2.964	3.25	9.797

Table 10. One sample statistics for work intensity (T1) for subject service.

		Statistic	Bootstrap a			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work intensity T1	N	11				
	Mean	1.5682	−0.0011	0.0875	1.3889	1.7308
	SD	0.29772	−0.01935	0.05714	0.19997	0.34553
	SE Mean	0.08977				

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Test							
	Test Value = 1.75						
	t	Df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
work intensity T1	−2.025	10	0.035	0.070	−0.18182	−0.3818	0.0182

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work intensity T1	−0.18182	−0.00114	0.08755	−0.36111	−0.01923

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work intensity T1	Cohen's d	0.29772	−0.611	−1.245	0.049
	Hedges' correction	0.32264	−0.564	−1.149	0.045

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 11. One sample statistics for work intensity (T2) for subject service.

		Statistic	Bootstrap b			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work intensity T2	N	11				
	Mean	2.4318	−0.0030	0.1273	2.2290	2.6538
	SD	0.43432	−0.02850	0.08404	0.29830	0.50000
	SE Mean	0.13095				

b. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Test							
	Test Value = 2.50						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
work intensity T2	−0.521	10	0.307	0.614	−0.06818	−0.3600	0.2236

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work intensity T2	−0.06818	−0.00278b	0.12673b	−0.27209b	0.15256b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 996 samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work intensity T2	Cohen's d	0.43432	−0.157	−0.748	0.442
	Hedges' correction	0.47069	−0.145	−0.690	0.408

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 12. One sample statistics for work intensity (T3) for subject service.

		Statistic	Bootstrap b			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work intensity T3	N	11				
	Mean	1.3864	0.0014	0.1188	1.1546	1.6250
	SD	0.40871	−0.02002	0.04497	0.35453	0.42743
	SE Mean	0.12323				

b. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Test							
	Test Value = 1.75						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided p	Two-Sided p		Lower	Upper
work intensity T3	−2.951	10	0.007	0.015	−0.36364	−0.6382	−0.0891

Bootstrap for One-Sample Test						
	Mean Difference	Bootstrap a				
		Bias	SE	Sig. (2-tailed)	BCa 95% Confidence Interval	
					Lower	Upper
work intensity T3	−0.36364	0.00181b	0.11823b	0.023b	−0.59333b	−0.12500b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 999 samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work intensity T3	Cohen's d	0.40871	−0.890	−1.580	−0.169
	Hedges' correction	0.44293	−0.821	−1.457	−0.156

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 13. One sample statistics for work complexity (T1) for subject service.

		Statistic	Bootstrap a			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work complexity T1	N	11				
	Mean	1.9318	0.0046	0.1322	1.7000	2.1944
	SD	0.44848	−0.02443	0.08150	0.30619	0.53452
	SE Mean	0.13522				

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Test							
	Test Value = 1.75						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
work complexity T1	1.345	10	0.104	0.208	0.18182	−0.1195	0.4831

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work complexity T1	0.18182	0.00463	0.13222	−0.05000	0.44444

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work complexity T1	Cohen's d	0.44848	0.405	−0.220	1.013
	Hedges' correction	0.48603	0.374	−0.203	0.934

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 14. One sample statistics for work complexity (T2) for subject service.

		Statistic	Bootstrap a			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work complexity T2	N	11				
	Mean	2.3409	0.0004	0.1353	2.1250	2.5750
	SD	0.46466	−0.03358	0.08723	0.32733	0.52968
	SE Mean	0.14010				

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Test							
	Test Value = 2.25						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided p	Two-Sided p		Lower	Upper
work complexity T2	0.649	10	0.266	0.531	0.09091	−0.2213	0.4031

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work complexity	0.09091	0.00038	0.13531	−0.12500	0.32500

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work complexity T2	Cohen's d	0.46466	0.196	−0.406	0.788
	Hedges' correction	0.50356	0.181	−0.375	0.727

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 15. One sample statistics for work complexity (T3) for subject service.

		Statistic	Bootstrap b			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work complexity T3	N	11				
	Mean	1.6818	−0.0096	0.1534	1.3958	1.9706
	SD	0.51346	−0.03049	0.09537	0.34686	0.60002
	SE Mean	0.15481				

b. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Test							
	Test Value = 1.75						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
work complexity T3	−0.440	10	0.335	0.669	−0.06818	−0.4131	0.2768

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work complexity T3	−0.06818	−0.00943b	0.15342b	−0.35417b	0.22135b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 999 samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work complexity T3	Cohen's d	0.51346	−0.133	−0.723	0.464
	Hedges' correction	0.55644	−0.123	−0.667	0.428

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 16. One sample statistics for time latitude (T1) for subject service.

		Statistic	Bootstrap a			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
time latitude T1	N	11				
	Mean	3.2045	−0.0090	0.2390	2.6596	3.6816
	SD	0.80482	−0.06948	0.19022	0.48412	0.98383
	SE Mean	0.24266				

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Test							
	Test Value = 2.75						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided p		Lower	Upper
time latitude T1	1.873	10	0.045	0.091	0.45455	−0.0861	0.9952

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
time latitude T1	0.45455	−0.00898	0.23896	−0.09039	0.93160

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
time latitude T1	Cohen's d	0.80482	0.565	−0.087	1.192
	Hedges' correction	0.87220	0.521	−0.080	1.100

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 17. One sample statistics for time latitude (T2) for subject service.

		Statistic	Bootstrap a			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
time latitude T2	N	11				
	Mean	3.0682	0.0019	0.1518	2.7778	3.3611
	SD	0.50114	−0.02963	0.07912	0.38193	0.56262
	SE Mean	0.15110				

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Test							
	Test Value = 2.75						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
time latitude T2	2.106	10	0.031	0.061	0.31818	−0.0185	0.6548

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
time latitude T2	0.31818	0.00190	0.15180	0.02778	0.61111

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
time latitude T2	Cohen's d	0.50114	0.635	−0.030	1.274
	Hedges' correction	0.54309	0.586	−0.027	1.175

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 18. One sample statistics for time latitude (T3) for subject service.

		Statistic	Bootstrap a			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
time latitude T3	N	11				
	Mean	3.4545	−0.0155	0.2491	2.9770	3.9066
	SD	0.84275	−0.05132	0.16392	0.59667	0.98638
	SE Mean	0.25410				

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Test							
	Test Value = 2.75						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
time latitude T3	2.773	10	0.010	0.020	0.70455	0.1384	1.2707

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
time latitude T3	0.70455	−0.01545	0.24913	0.22698	1.15662

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
time latitude T3	Cohen's d	0.84275	0.836	0.128	1.514
	Hedges' correction	0.91331	0.771	0.118	1.397

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 19. One sample statistics for work intensity (T1) for nutrition.

		Statistic	Bootstrap c			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work intensity T1	N	7				
	Mean	3.5714	0.0011	0.1759	3.1694	3.8923
	SD	0.44987	−0.05694d	0.13035d	0.22835d	0.53348d
	SE Mean	0.17003				

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; d. Based on 998 samples.

One-Sample Test

	Test Value = 3.25						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
work intensity T1	1.890	6	0.054	0.108	0.32143	−0.0946	0.7375

Bootstrap for One-Sample Test

	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work intensity T1	0.32143	0.00165b	0.17064b	−0.06250b	0.62500b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 993 samples.

One-Sample Effect Sizes

		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work intensity T1	Cohen's d	0.44987	0.714	−0.147	1.532
	Hedges' correction	0.51791	0.621	−0.128	1.331

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 20. One sample statistics for work intensity (T2) for nutrition.

		Statistic	Bootstrap c			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work intensity T2	N	7				
	Mean	3.3571	0.0052	0.1071	3.1500	3.6250
	SD	0.28347	−0.02951d	0.07681d	0.20863d	0.31339d
	SE Mean	0.10714				

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; d. Based on 997 samples.

One-Sample Test							
	Test Value = 3.25						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided p	Two-Sided p		Lower	Upper
work intensity T2	1.000	6	0.178	0.356	0.10714	−0.1550	0.3693

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work intensity T2	0.10714	0.00729b	0.10346b	−0.08333bc	0.33333b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 960 samples; c. Some results could not be computed from jackknife samples. so this confidence interval is computed by the percentile method rather than the BCa method.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work intensity T2	Cohen's d	0.28347	0.378	−0.406	1.134
	Hedges' correction	0.32635	0.328	−0.353	0.985

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 21. One sample statistics for work intensity (T3) for nutrition.

		Statistic	Bootstrap c			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work intensity T3	N	7				
	Mean	2.9643	0.0065	0.2245	2.5000	3.4105
	SD	0.60257	−0.06649d	0.14114d	0.37884d	0.67997d
	SE Mean	0.22775				

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; d. Based on 996 samples.

One-Sample Test							
	Test Value = 3.25						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided p	Two-Sided p		Lower	Upper
work intensity T3	−1.255	6	0.128	0.256	−0.28571	−0.8430	0.2716

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work intensity T3	−0.28571	0.00576b	0.22049b	−0.75000b	0.14286b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 992 samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work intensity T3	Cohen's d	0.60257	−0.474	−1.243	0.329
	Hedges' correction	0.69371	−0.412	−1.080	0.286

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 22. One sample statistics for work complexity (T1) for nutrition.

		Statistic	Bootstrap c			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work complexity T1	N	7				
	Mean	3.1786	0.0091	0.1954	2.6927	3.4643
	SD	0.53452	−0.11739d	0.24807d	0.11573d	0.72169d
	SE Mean	0.20203				

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; d. Based on 998 samples.

One-Sample Test							
	Test Value = 3.00						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided p	Two-Sided p		Lower	Upper
work complexity T1	0.884	6	0.205	0.411	0.17857	−0.3158	0.6729

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work complexity T1	0.17857	0.00422b	0.19444b	−0.29167b	0.44447b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 975 samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work complexity T1	Cohen's d	0.53452	0.334	−0.442	1.085
	Hedges' correction	0.61537	0.290	−0.384	0.942

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 23. One sample statistics for work complexity (T2) for nutrition.

		Statistic	Bootstrap c			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work complexity T2	N	7				
	Mean	3.2143	0.0027	0.2395	2.7857	3.7500
	SD	0.63621	−0.06857d	0.14954d	0.41904d	0.71651d
	SE Mean	0.24046				

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; d. Based on 998 samples.

One-Sample Test							
	Test Value = 3.00						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
work complexity T2	0.891	6	0.204	0.407	0.21429	−0.3741	0.8027

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work complexity T2	0.21429	0.00264b	0.23670b	−0.20895b	0.75000b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 997 samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work complexity T2	Cohen's d	0.63621	0.337	−0.440	1.088
	Hedges' correction	0.73243	0.293	−0.382	0.945

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 24. One sample statistics for work complexity (T3) for nutrition.

		Statistic	Bootstrap c			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
work complexity T3	N	7				
	Mean	2.8929	−0.0013	0.1899	2.5833	3.2500
	SD	0.49701	−0.06310d	0.13661d	0.27386d	0.58384d
	SE Mean	0.18785				

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; d. Based on 997 samples.

One-Sample Test							
	Test Value = 3.00						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
work complexity T3	−0.570	6	0.295	0.589	−0.10714	−0.5668	0.3525

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
work complexity T3	−0.10714	−0.00190b	0.18750b	−0.41667b	0.25000b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 990 samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
work complexity T3	Cohen's d	0.49701	−0.216	−0.957	0.543
	Hedges' correction	0.57218	−0.187	−0.832	0.472

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 25. One sample statistics for time latitude (T1) for nutrition.

		Statistic	Bootstrap c			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
time latitude T1	N	7				
	Mean	2.8214	−0.0094	0.4089	1.9643	3.6250
	SD	1.09653	−0.10725d	0.22792d	0.90370d	1.12547d
	SE Mean	0.41445				

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; d. Based on 995 samples.

One-Sample Test							
	Test Value = 3.25						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
time latitude T1	−1.034	6	0.170	0.341	−0.42857	−1.4427	0.5856

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
time latitude T1	−0.42857	−0.01876b	0.39008b	−1.29167bc	0.25000b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 983 samples; c. Some results could not be computed from jackknife samples. So this confidence interval is computed by the percentile method rather than the BCa method.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
time latitude T1	Cohen's d	1.09653	−0.391	−1.148	0.395
	Hedges' correction	1.26237	−0.339	−0.997	0.343

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 26. One sample statistics for time latitude (T2) for nutrition.

		Statistic	Bootstrap c			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
time latitude T2	N	7				
	Mean	2.6429	−0.0032	0.2980	2.0357	3.1786
	SD	0.77536	−0.08091d	0.15854d	0.62249d	0.80364d
	SE Mean	0.29306				

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; d. Based on 996 samples.

One-Sample Test							
	Test Value = 3.25						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
time latitude T2	−2.072	6	0.042	0.084	−0.60714	−1.3242	0.1099

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
time latitude T2	−0.60714	0.00189b	0.28478b	−1.16813b	−0.07143b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 987 samples.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
time latitude T2	Cohen's d	0.77536	−0.783	−1.618	0.098
	Hedges' correction	0.89263	−0.680	−1.405	0.085

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Table 27. One sample statistics for time latitude (T3) for nutrition.

		Statistic	Bootstrap c			
			Bias	SE	BCa 95% Confidence Interval	
					Lower	Upper
time latitude T3	N	7				
	Mean	2.9643	−0.0079	0.2169	2.5833	3.3571
	SD	0.58503	−0.06205d	0.13928d	0.42956d	0.63649d
	SE Mean	0.22112				

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; d. Based on 997 samples.

One-Sample Test							
	Test Value = 3.25						
	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided *p*	Two-Sided *p*		Lower	Upper
time latitude T3	−1.292	6	0.122	0.244	−0.28571	−0.8268	0.2553

Bootstrap for One-Sample Test					
	Mean Difference	Bootstrap a			
		Bias	SE	BCa 95% Confidence Interval	
				Lower	Upper
time latitude T3	−0.28571	−0.00824b	0.21335b	−0.70833bc	0.15000b

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples; b. Based on 992 samples; c. Some results could not be computed from jackknife samples. So this confidence interval is computed by the percentile method rather than the BCa method.

One-Sample Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
time latitude T3	Cohen's d	0.58503	−0.488	−1.259	0.318
	Hedges' correction	0.67351	−0.424	−1.094	0.276

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Group Statistics							
	Observation group		Statistic	Bootstrap a			
				Bias	Std. Error	BCa 95% Confidence Interval	
						Lower	Upper
Standardised effect size	Patient-care	N	9				
		Mean	0.5632	0.0022	0.0648	0.4450	0.7047
		Std. Deviation	0.19760	−0.01711	0.05134	0.07871	0.24067
		Std. Error Mean	0.06587				
	Nutrition	N	9				
		Mean	0.6985	0.0010	0.0844	0.5502	0.8699
		Std. Deviation	0.26254	−0.02846	0.07870	0.12139	0.32935
		Std. Error Mean	0.08751				

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

Independent Samples Test											
		Levene's Test for Equality of Variances		t-test for Equality of Means							
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						One-Sided *p*	Two-Sided *p*			Lower	Upper
Effect_size	Equal variances assumed	0.160	0.694	−1.235	16	0.117	0.235	−0.13528	0.10953	−0.36747	0.09691
	Equal variances not assumed			−1.235	14.862	0.118	0.236	−0.13528	0.10953	−0.36893	0.09837

Comparing outcomes between teams, the average standardised effect size for all team nutrition comparisons at g = 0.698 was larger than for the average standardised effect for all team subject service comparisons g = 0.563. This difference was tested in a subsequent analysis and was found to be small and not significant (see Table 28 and Table 29).

Table 28. Bootstrap for independent samples t-test comparing convergence effect sizes between subject service and nutrition.

		Mean Difference	Bootstrap a				
			Bias	Std. Error	Sig. (2-tailed)	BCa 95% Confidence Interval	
						Lower	Upper
Effect_size	Equal variances assumed	−0.13528	0.00121	0.10588	0.228	−0.35835	0.06877
	Equal variances not assumed	−0.13528	0.00121	0.10588	0.238	−0.35835	0.06877

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples.

Independent Samples Effect Sizes					
		Standardiser a	Point Estimate	95% Confidence Interval	
				Lower	Upper
Effect_size	Cohen's d	0.23235	−0.582	−1.519	0.372
	Hedges' correction	0.24400	−0.554	−1.446	0.354
	Glass's delta	0.26254	−0.515	−1.457	0.456

a. The denominator used in estimating the effect sizes. Cohen's d uses the pooled standard deviation. Hedges' correction uses the pooled standard deviation, plus a correction factor. Glass's delta uses the sample standard deviation of the control group.

Table 29. Dropout analysis to test attrition bias (ANOVA).

		Sum of Squares	df	Mean Square	F	Sig.
Work intensity T1	Between Groups	0.906	1	0.906	0.789	0.381
	Within Groups	36.765	32	1.149		
	Total	37.671	33			
Work complexity T1	Between Groups	0.557	1	0.557	0.605	0.443
	Within Groups	29.460	32	0.921		
	Total	30.017	33			
Time latitude T1	Between Groups	0.372	1	0.372	0.464	0.501
	Within Groups	25.654	32	0.802		
	Total	26.026	33			
Need for recovery T1	Between Groups	0.026	1	0.026	0.216	0.646
	Within Groups	3.804	32	0.119		
	Total	3.830	33			
Psychological detachment T1	Between Groups	1.018	1	1.018	1.184	0.285
	Within Groups	27.521	32	0.860		
	Total	28.539	33			

Robust Tests of Equality of Means					
		Statistic	df1	df2	Sig.
Work intensity T1	Welch	0.752	1	13.598	0.401
Work complexity T1	Welch	0.654	1	15.303	0.431
Time latitude T1	Welch	0.542	1	16.568	0.472
Need for recovery T1	Welch	0.194	1	12.965	0.667
Psychological detachment T1	Welch	1.192	1	14.277	0.293

5. Discussion

5.1. Strain Effects

Support for the strain hypothesis 1 (a/b) differs between work factors and on the context of analysis. Work intensity has the clearest pattern of effects. It shows to be negatively correlated with psychological detachment and to be positively correlated with need for recovery. The regressions show that these main effects remain significant when controlling for other working conditions and prior fatigue. It can be interpreted that increased work intensity predicts increased later need for recovery and decreased later psychological detachment. This supports the strain hypothesis 1 (a), stating demands to positively predict later fatigue. Comparisons with the existing body of literature are limited, as the present study is one of few attempts to test strain effects with a three-waves design, using comparable time lags. Work intensity predicting need for recovery confirms what Sonnentag & Zijlstra (2006) showed; quantitative workload predicting need for recovery. However, comparability between these studies is low since the authors used daily surveying over five days and did not measure symptoms of need for recovery. Instead, they measured if participants felt they had enough opportunity to recover. Effects of work intensity are also congruent with De Raeve et al. (2007), though comparability is lowered by the large difference in time lags. Yet, it indicates that the exposure time necessary to affect need for recovery is shorter than demonstrated by De Raeve et al. (2007). Work intensity negatively predicting psychological detachment measured 2 - 3 weeks later, supports previous findings, that show psychological detachment predicted by work demands on a day level (Sonnentag & Bayer, 2005) and after 2 months (Dettmers, 2017). It also indicates that working conditions from previous 2 - 3 weeks predict psychological detachment, and that an exposure time of 2 months is not required to affect psychological detachment. Another noteworthy insight is that the prediction of psychological detachment occurred more short-term than effects on need for recovery, since psychological detachment was predicted by time two variables (a lag of approximately 23 days), while need for recovery was predicted by time one variables (a lag of approximately 46 days). This shows that the minimum exposure time to affect psychological detachment can be shorter than the minimum exposure time to affect need for recovery.

Considering longitudinal meta-analytic strain effects on burnout (Lesener et al., 2019), the current results regarding work intensity are congruent. Bivariate effect sizes of work intensity and later fatigue are generally comparable with meta-analytic correlations by Lesener et al. (2019). Comparisons of standardised coefficients are limited by the suppression effects. Still, the amount of explained variance is comparable to the meta-analytic model, explaining 48% of the variance in burnout (Lesener et al., 2019), while the present study explains 40% of adjusted variance of need for recovery and 57% of adjusted variance of psychological detachment. However, stabilities are lower than in the meta-analytic model. This decreases the relevance of effects (Adachi & Willoughby, 2015). Yet, it is unsurprising that short-term fatigue shows less stability than chronic fatigue, and that one's ability to psychologically detach from work fluctuates higher than burnout. It also needs to be considered, that the workers within this sample underwent work changes when bed-rest-study phases changed, which may have affected stability of the fatigue variables.

Work complexity, the second demand tested in this study, shows to affect fatigue differently, depending on the context of the analysis. Bivariate correlations indicate that high work complexity is near-significantly associated with high need for recovery at later time frames, and significantly associated with low psychological detachment at later time frames. This implies high work complexity to be correlated with high fatigue and supports hypothesis 1 (a). However, when regressively analysing the effects of work complexity in an extended context (controlling for other working conditions and interactions), the direction of effects reverses. Based on the step one regression analysis, increased work complexity is associated with reduced need for recovery. This near-significant effect gets reduced further when controlling for time two need for recovery and time two working conditions. Effects of work complexity predicting psychological detachment are smaller, showing no indication of significance when controlling for the other working conditions. Nonetheless, the direction of effects also reverses in this instance. This contradicts strain hypothesis 1 (a), because effects lack significance when controlling for other working conditions and are directed contrary to the hypothesis. It conveys that if work intensity, time latitude, and the interactions are controlled for, increased work complexity shows a trend to decrease need for recovery, which implies a beneficial main effect and cannot be defined as strain.

Only the bivariate correlations are therefore in line with previous findings on demands predicting increased fatigue (De Raeve et al., 2007; Dettmers, 2017; Lesener et al., 2019; Sonnentag & Zijlstra, 2006); the regression coefficient indicating decreases in fatigue are contrary. From the JDCS perspective it would be not surprising to find work complexity showing a fatigue reducing effect if control is high, as this combination qualifies as an active job (Karasek, 1979). However, it is surprising that work complexity predicts decreased need for recovery as a main effect, when controlling for time latitude and interactions, since controlling for these factors isolates the relationship of work complexity and the outcome. Prior reviews (Fila et al., 2013; Häusser et al., 2010; Lesener et al., 2019) did not focus on work complexity though but measured mostly quantitative workload. The current results should thus be interpreted as findings on another predictor, not a contradiction. The deviation hints, that work complexity affects strain differently than other demands, like work intensity, and should therefore be reviewed thoroughly. Work complexity, according to Sonntag & Feldmann (2022), is ideally kept on a moderate level, as both low and high complexity could be straining. This signifies a U-shape relationship between work complexity and fatigue, and it has been tested cross-sectionally (Chung-Yan, 2010). Contrary to the present study, the author found no significant bivariate correlation between work complexity and the strain variable (psychological wellbeing). He concluded that work complexity can both positively and negatively predict wellbeing when autonomy is low or moderate, with moderate complexity being ideal for wellbeing. In addition, the study showed that, if autonomy was high, any level of work complexity predicted equal wellbeing levels (Chung-Yan, 2010). Applying these findings to the present study, a key take away should be that main effects of work complexity seem to depend on whether the factor is analysed bivariately or in the context of other factors. While a conclusive comparison is limited due to the different study design used by Chung-Yan (2010), and due to autonomy not being measured as time latitude, comparing these findings shows that there is agreement about work complexity's effects being context dependent.

Adding insights from Bai et al. (2021), it may be useful to consider their dual-path mediation model within the Conservation of Resources theory (Holmgreen et al., 2017). This model suggests that work complexity can lead to both resource gain (via increased work engagement) and resource loss (via energy depletion), influencing job crafting behaviors. This dual perspective aligns with the current finding that increased work complexity can be associated with reduced or increased need for recovery. The resource gain process through enhanced engagement can explain this beneficial effect, supporting the notion that higher job complexity can foster proactive job crafting, enhancing employee resources and reducing fatigue. On the one hand, this may contribute to explaining the current findings on work complexity predicting decreased later need for recovery. On the other hand, the short time frame, the current study was conducted in, weakens this explanation. Because participants may not have had sufficient time for job crafting. Based on that, work complexity cannot be stated to have a clear fatigue increasing or decreasing, but a context dependent effect, necessitating further investigation of moderating and mediating factors.

Time latitude, the included control variable, also shows context-dependent effects and requires nuanced interpretations. Time latitude shows reversed predictive effects for psychological detachment when other working conditions are controlled for. For need for recovery, no reversal was found, but controlling for other working conditions renders main effects insignificant. Predictive effects thus vary from bivariate relationships, as time latitude is negatively correlated with need for recovery at later time frames, and slightly positively correlated with psychological detachment. These bivariate effects are congruent with strain hypothesis 1 (b), suggesting control to negatively predict fatigue. The bivariate correlations with need for recovery are in line with the previous result, that decision latitude, also a control factor, longitudinally predicts decreased need for recovery (De Raeve et al., 2007). The regression effects observed in the present study, regarding the relationship between time latitude and later need for recovery, do not confirm these findings, due to the lack of statistical significance in the current coefficients. Still, it is crucial to consider the difference in sample sizes when comparing these analyses. The present study had 25 subjects, while the research by De Raeve et al. (2007) had 2332 subjects. The authors report decreased need for recovery due to decision latitude of $\beta = -0.078$, which is significant, albeit of such small magnitude, that the present study could not have detected it due to its low power.

When regressively analysing psychological detachment, time latitude shows a near-significant negative effect when controlling for the other working conditions and interactions. This finding contradicts hypothesis 1 (b), and therefore suggests that, when influences of other working conditions are controlled for, increased time latitude is associated with decreased ability to psychologically detach from work. The negative prediction of psychological detachment does not oppose the stressor-detachment framework, as the model does not describe main effects of control. Still, the authors (Sonnentag & Fritz, 2015) describe how psychological detachment could be inhibited by a lack of job resources. Therefore, the current finding insinuates deviation from the theory. Thus, only bivariate results regarding time latitude and psychological detachment are congruent witch cross-sectional correlations reported previously (Ward & Steptoe-Warren, 2013). When controlling for the other working conditions and interactions, the near-significant negative prediction of psychological detachment opposes the previous positive effects. Inconsistent main effects of job control have been discussed by Kubicek et al. (2014), who found curvilinear relationships cross-sectionally and longitudinally. A comparison with these results can be valuable for interpreting the current effects, as both studies drew subjects from similar industries. The authors discuss whether control could increase fatigue, when exerting job control is perceived as a necessity, not an opportunity and thus becomes a demand. Increased job control could also be coupled with increased responsibilities leading to ruminations about work during non-work time (Kubicek et al., 2014). Building on these argumentations, a decrease in one's ability to psychologically detach from work is attributable to workers with high control over their work time who think more often about their work due to a) more planning efforts when scheduling work during free time and b) feeling obliged to be more involved in their work as they know they are given the privilege of time latitude and want to restore equity (Gould, 1979).

5.2. Buffer Effects

The interaction effects generally support the hypotheses 2 (a) and (b), predicting that the matching quality of demands and control affects buffering. The current findings will be discussed in the context of previous research, after interpreting the nature of the interactions.

The interaction of work intensity and time latitude, the good match, significantly negatively predicts later need for recovery. As theoretically suggested by the buffer hypothesis, this negative interaction effect can be interpreted as time latitude buffering the increasing effect of work intensity on need for recovery. Note that when interpreting interaction terms, no direct indication is provided on which variable is the moderator. For psychological detachment, findings are analogous to need for recovery. The interaction of work intensity and time latitude predicts psychological detachment near significantly, marginally missing the 5% significance. This positive interaction effect can be interpreted as time latitude buffering the decreasing effect of work intensity on psychological detachment.

The bad match, the interaction of work complexity and time latitude, does not consistently predict fatigue. No significant effects were found on psychological detachment, or in the full (step two) model of need for recovery. The only instance of significance is the step one model predicting need for recovery. This effect does not remain significant when controlling for time two variables. Beyond that, the effect poses interpretative challenges. The positive interaction effect can be interpreted as time latitude buffering the negative main effect of work complexity on need for recovery. As any interaction can be interpreted both ways, work complexity could also moderate the main effect of time latitude. According to the JDCS and the result that time latitude only shows minuscule main effects on later need for recovery, interpreting time latitude to be the moderator seems more relevant. Work complexity reveals a near-significant negative effect on need for recovery in the step one model. Buffering this main effect signifies that the beneficial effect of work complexity is diminished when time latitude is increased. Technically, this is buffering. Yet, the buffer-hypothesis is associated with control buffering detrimental effects of demands (Van der Doef & Maes, 1999), not with an attenuation of beneficial effects. Time latitude diminishing beneficial effects of demands opposes how Karasek (1979) described active work to increase wellbeing. It further opposes the empirical finding that work complexity at any level is associated with increased wellbeing if autonomy is high (Chung-Yan, 2010). Not challenging the assumptions of the JDCS, an argument can still be made for how high time latitude could attenuate beneficial effects of work complexity in some instances; exerting time latitude inappropriately may lead to frequent task switching or multi-tasking. This is associated with performance costs (Ward et al., 2019), and may detract from engaging deeply with complex tasks, thus decreasing its benefits. This job-enrichment-gone-wrong-perspective is a preliminary attempt to explain the deviating results while not opposing the JDCS.

In conclusion, since buffer effects as described within the JDCS (Johnson & Hall, 1988; Karasek, 1979), only occurred when demands and control were matched well, the present study confirms the importance of the matching principle as previously stated (de Jonge & Dormann, 2006; Häusser et al., 2010; Jonge & Dormann, 2003). Yet, this research extends prior implications. It adds that the matching principle applies when predicting early fatigue indicators. Beyond that, it demonstrates that matching entails aspects besides classifying variables as physical, emotional, or cognitive (Jonge & Dormann, 2003), as time latitude consistently buffers work intensity, but not work complexity. This control facet is described as cognitive rather than physical or emotional, as it entails planning and decision-making regarding work processes (Sonntag & Feldmann, 2022). Work intensity can be argued to either be cognitive, physical, or emotional, depending on the nature of the tasks, as the construct refers to the imposed load of tasks (Sonntag & Feldmann, 2022). Work complexity though is described as cognitive, as it necessitates information processing (Sonntag & Feldmann, 2022). Despite the control factor being primarily cognitive, it does not show to consistently buffer the purest cognitive demand. It can further be stated, that the one buffer effect, which was found despite poor matching, does not correspond to the theory of buffering and is less clearly interpretable than buffer effects from well-matched variables.

5.3. Convergence

Considering the 10,48% average difference between subjective and objective scores, and that two thirds of the comparisons detected no significant differences, hypothesis 3 (a) and (b) are partially supported. Interpreting the results separately for work intensity, work complexity and time latitude reveals the highest support for convergence for work complexity scores, lower support for work intensity scores, and lowest support for time latitude scores. This is the first attempt to test convergence for these measurements, through mean comparisons and using identical item contents between objective and subjective measures. The current results are thus not directly comparable to previous convergence findings (Melamed et al., 1995; Stab et al., 2016). It is still noteworthy that on average, current subjective and objective scores are 89,52% congruent, while correlations between objective and subjective scores by Melamed et al. (1995) explained on average 8% of variance, and correlations by Stab et al. (2016) explained at maximum 25% of variance. This comparison implies that the identical item contents contributed largely to convergence. Beyond that, the pattern of current results holds further implications.

The finding that subjective scores were equally often higher or lower than objective scores indicates that the subjective measurement did not systematically over- or underreport demands or control, compared to the objective measure. Subjective demands scores being consistently underreported compared to objective demands scores, and subjective control scores being consistently overreported compared to objective control scores, would suggest that the subjective scores were biased through social desirability or negative affectivity. As such patterns were not present for work intensity, work complexity, or time latitude, it can be inferred that no such biases strongly affected the scores. This does not rule out that strain scores were not biased. It however could indicate, that when subjective demands and control scores are not strongly biased, the subjective strain scores are not strongly biased either. This is due biasing factors like social desirability (Chen et al., 1997) and negative affectivity (Watson & Clark, 1984) being defined as traits which should have general effects on responding.

The current findings also show that convergence differs between working conditions, as the deviations for time latitude were three times higher than for work complexity, and 50% higher than for work intensity. Larger differences between objective and subjective time latitude scores, compared to work intensity and work complexity, can be attributed to how the factors were assessed during observations. As the study workers used various protocols and instructions for individual tasks, work intensity in terms of the number of tasks and the task density within a time frame was more directly observable. Protocols and instructions informed both observer and workers about what tasks had to be completed. Work complexity was specifically observable because workers had access to instructions that informed them about tasks requirements. Scheduling activities on the other hand may occur when workers are at home, so they are not observed directly and information regarding the ability to schedule one's workday is gathered through questioning. Subtle changes in work pace may be missed by the observer, or changes in work pace may be perceived as intentional adjustments when they are not. This demonstrates how observing time latitude may be more prone to error and can explain lower convergence compared to work intensity and work complexity that were observable based on more salient indicators.

5.4. Limitations and Strengths

The three-wave longitudinal design was more internally valid and capable for testing causation than cross-sectional studies (Kain & Jex, 2010). Using three waves enabled testing two different time lags and these lags were set appropriately for the short-term fatigue variables. Measuring all variables at every time frame allowed to control for stabilities and increased internal validity (Lesener et al., 2019). The triple measuring of demands and control across two teams also benefitted testing convergence, as effects for the same constructs were assessed repeatedly. Triple convergence testing thus provided more reliable insight than comparing objective and subjective scores cross-sectionally. Three waves also allowed to assess reliabilities repeatedly, which was particularly useful, as the demand and control scales have not yet been tested in this survey format. While most internal scale consistencies can be described as good, the reliability of the short form need for recovery scale can be criticised for missing the reliability criterion at each time frame. This impacts the internal validity of the results on need for recovery and the three-wave design leastwise provided repeated inside into the scales' reliability.

The present study was moreover limited in the number of measures it deployed, in favour of low dropout rates. Measuring different demands was prioritised as it permitted valuable insight into buffering and matching. The narrow scope meant not measuring factors that could bias responses, like social desirability (Chen et al., 1997) and negative affectivity (Watson & Clark, 1984). As gender and nationality were not measured either, the present study was unable to control for these factors and test moderation effects like prior research (Fila et al., 2017), limiting the interpretability of the current findings due to potential confounding effects. The interpretation of the results is further limited by the fact, that the current study did not include other control variables. On the positive, the study showed that objective and subjective scores converged highly and that no pattern indicated over- or underreporting of scores in one type of measurement. This supports that subjects did not respond strongly biased. The low dropout rate of 26% compared to similar research using three-waves (Dettmers, 2017) is also positive and, paired with the dropout analysis, contributes to a good method (Lesener et al., 2019).

The low sample size marks a limitation, as it decreased power, resulting in increased probabilities of overfitting and limits the generalisability of the results. While statistical countermeasures like bootstrapping were used to address sample limitations, not all drawbacks were attenuated. This limits comparisons with studies using large samples, that detected small effects (De Raeve et al., 2007), while in the present study moderate effects often missed criteria of significance. Despite the small sample size, the present study found significant strain and buffer effects, which attests the size of effects. While the sample was limited in size, the study included multiple different teams. This strengthens external validity and suggests that the findings can be generalised to more than a single job type. On the other hand, the sample was not representative for the working population. Due to the absence of demographic data, an accurate description of the sample could not be given, however representativeness was not achieved considering the sample size of 25 subjects.

Measuring demands and control objectively and subjectively is a strength of this research because it addresses this aspect, overlooked by many studies (Lesener et al., 2019). This strength is reinforced by applying the observational measures longitudinally. Moreover, adapting the observation measures provided new insight into how convergence can be increased if item contents are kept identical to enable comparable results. It is however necessary to consider, that the observations were limited to a single observer who was not blind to the goals of the study (Burghardt et al., 2012). A single observer also disabled using the instrument in its original consensus-oriented way (Sonntag & Feldmann, 2022). Despite the scores from the workplace observation being defined as the objective scores, complete objectivity can therefore be questioned, as observer biases cannot be rejected. The objective scores can thus not be regarded as fully objective, and scores may be more biased than scores produced by studies with multiple observers (Stab et al., 2016). Beyond objectivity, using a single observer may increase error rates, through missed events, especially under high cognitive load (Reyes & Lee, 2008). The design of the observations is therefore a strength, while limitations exist within the execution.

5.5. Implications

Replicating the present study with more extensive resources can advance future research. A large sample of a least 30 workplaces would be viable for multilevel hierarchical modelling (van Dick et al., 2005) and would increase statistical power, leading to more robust findings on fatigue and convergence. A replication should use a more representative workplace sample to test how effects differ between job types as put forward by Bakker & Demerouti (2007). Large samples entail using a team of observers for objective workplace data. The present study adapted only a fraction of GPB dimensions for its survey and future studies can deploy the full measure in an adapted survey format. As effects have been shown to be context-dependent, using all 13 work dimensions within a large sample can capture multivariate complexity better by using structural equation modelling (Ullman & Bentler, 2012). Current issues with the reliability of the short need for recovery scale may be avoided by using the full scale (Veldhoven, 2008) in future applications.

Divergent findings on work complexity and time latitude require additional attention. Future goals should be to explain under which conditions work complexity can reduce need for recovery, and if main effects are robust. Time latitude attenuating positive effects of work complexity should be reinvestigated regarding how people choose to manage their work time when dealing with complex tasks. The difference in exposure time between need for recovery and psychological detachment should be subject to further research to find out whether effects on these variables correspond to different stressor-strain models (Garst et al., 2000) or whether mechanisms are similar, but require different durations of exposure. This includes testing how effects change with exposure time, whether adaption decreases effects or whether accumulation sustains or increases effects (Frese & Zapf, 1988). Reversed causation (Garst et al., 2000), the paths of need for recovery, and psychological detachment predicting later working conditions should be addressed in future research, as the parameters of this study (highly standardised job roles and a short time frame) were ineffective in testing whether fatigued workers drift into worse working conditions or refuge into better ones.

For practitioners, a key take away should be that both strain and buffer effects are relevant for fatigue effects in the workplace. This is crucial because the strain and buffer hypotheses impose different practical applications (Van der Doef & Maes, 1999). Redesigning work according to the buffer hypothesis means that increasing control would eliminate all adverse effects of high demands, whereas according to the strain hypothesis, not all negative effects can be resolved by increasing control (Karasek & Theorell, 1990, as cited in Fila, 2016). Based on work intensity showing robust fatigue-increasing main effects, it is recommended to reduce high work intensity. Time latitude consistently showed to attenuate some, but not all adverse effects of work intensity. This should be utilised by enabling employees to decide when they are doing their tasks, to prioritise them, and to change their working speed accordingly (Sonntag & Feldmann, 2022). However, findings imply that increasing time latitude cannot buffer work intensity fully, and that time latitude does not reduce fatigue directly. Reducing time pressure and the necessity to work on parallel tasks or postponement of work steps should thus remain a primary concern, with time latitude being another vector of fatigue reduction. Time latitude showing tendencies of unwanted effects does not justify reducing or disregarding interventions that increase time latitude, because the positive effects prove to be substantially more robust. Still, the findings on potentially adverse effects are useful for practitioners because they hint at possible shortcomings that should be avoided in practice. These concern the effect of time latitude decreasing beneficial effects from complex work, and time latitude decreasing the ability to psychologically detach from work. While definitive recommendations should not be made based on limited findings, practitioners should be aware that high time latitude may motivate frequent task switching, which lowers attention on tasks (Ward et al., 2019). This means that interventions should not only increase time latitude, but frame complex tasks as growth opportunities that deserve dedicated time and energy. Concerning time latitude possibly decreasing psychological detachment due to planning activities during non-work hours, it can be recommended to provide not only efficient planning tools, but to enable employees to pursue planning and scheduling during working hours. Practitioners should also consider that employees may feel obliged to stay non-detached from work when they have been granted time latitude to restore equity with the organisation (Gould, 1979). The responsibility lies with the leadership to encourage relaxation and communicate that time latitude is not coupled with expectations of increased work involvement during leisure time. For accurate diagnosis, it is recommended to pair objective and subjective measures as demonstrated by the present study. Measures of fatigue, such as need for recovery or psychological detachment, can be deployed by practitioners to assess short-term fatigue changes. This assessment can then be used for a first evaluation of interventions, before an assessment of long-term effects becomes viable.

6. Conclusion

In conclusion, this study advances the research on how demands and control affect strain, by demonstrating short-term fatigue effects. The new findings close a research gap as they show how fatigue indicators, which are predictors of long-term strain, are affected in short-term by work intensity, work complexity, and time latitude. Based on previous takes on matching demands and control (Cohen & Wills, 1985; Jonge & Dormann, 2003), the matching principle is extended and re-evaluated. Based on its findings, this study stresses the importance of matching demands and control to be complementary for buffering effects to occur. Unexpected findings on main effects of work complexity, time latitude and their interaction received preliminary explanations that should be subjected to further studies. Finally, this study progresses research comparing objective and subjective scores of demands and control factors by showing how identical item contents may contribute to convergence compared to prior studies (Melamed et al., 1995; Stab et al., 2016). Adopting such dual measurements could enable more exhaustive measurements of working conditions.

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Data Availability

The data that support the findings of this paper are not openly available due to legal restrictions.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Adachi, P., & Willoughby, T. (2015). Interpreting Effect Sizes When Controlling for Stability Effects in Longitudinal Autoregressive Models: Implications for Psychological Science. *European Journal of Developmental Psychology, 12,* 116-128. https://doi.org/10.1080/17405629.2014.963549

Agarwal, H., & Vaghela, P. (2018). Work Values of Gen Z: Bridging the Gap to the Next Generation. In *National Conference on Innovative Business Management Practices in 21st Century* (pp. 1-26). Parul University.

Bai, J. Y., Tian, Q., & Liu, X. (2021). Examining Job Complexity on Job Crafting within Conservation of Resources Theory: A Dual-Path Mediation Model. *Frontiers in Psychology, 12,* Article 737108. https://doi.org/10.3389/fpsyg.2021.737108

Bakker, A. B., & Demerouti, E. (2007). The Job Demands-Resources Model: State of the Art. *Journal of Managerial Psychology, 22,* 309-328. https://doi.org/10.1108/02683940710733115

Bliese, P. D., Edwards, J. R., & Sonnentag, S. (2017). Stress and Well-Being at Work: A Century of Empirical Trends Reflecting Theoretical and Societal Influences. *Journal of Applied Psychology, 102,* 389-402. https://doi.org/10.1037/apl0000109

Burghardt, G. M., Bartmess-LeVasseur, J. N., Browning, S. A., Morrison, K. E., Stec, C. L., Zachau, C. E. et al. (2012). Perspectives—Minimizing Observer Bias in Behavioral Studies: A Review and Recommendations. *Ethology, 118,* 511-517. https://doi.org/10.1111/j.1439-0310.2012.02040.x

Chen, P. Y., Dai, T., Spector, P. E., & Jex, S. M. (1997). Relation between Negative Affectivity and Positive Affectivity: Effects of Judged Desirability of Scale Items and Respondents' Social Desirability. *Journal of Personality Assessment, 69,* 183-198. https://doi.org/10.1207/s15327752jpa6901_10

Chrisopoulos, S., Dollard, M. F., Winefield, A. H., & Dormann, C. (2010). Increasing the Probability of Finding an Interaction in Work Stress Research: A Two-Wave Longitudinal

Test of the Triple-Match Principle. *Journal of Occupational and Organizational Psychology, 83,* 17-37. https://doi.org/10.1348/096317909x474173

Chung-Yan, G. A. (2010). The Nonlinear Effects of Job Complexity and Autonomy on Job Satisfaction, Turnover, and Psychological Well-Being. *Journal of Occupational Health Psychology, 15,* 237-251. https://doi.org/10.1037/a0019823

Ciesielska, M., Boström, K.W., & Öhlander, M. (2018). Observation Methods. In: M. Ciesielska, & D. Jemielniak (Eds.), *Qualitative Methodologies in Organization Studies* (pp. 33-52). Palgrave Macmillan.

Cohen, S., & Wills, T. A. (1985). Stress, Social Support, and the Buffering Hypothesis. *Psychological Bulletin, 98,* 310-357. https://doi.org/10.1037/0033-2909.98.2.310

Cook, R. D., & Weisberg, S. (1982). *Residuals and Influence in Regression.* Chapman and Hall.

de Jonge, J., & Dormann, C. (2006). Stressors, Resources, and Strain at Work: A Longitudinal Test of the Triple-Match Principle. *Journal of Applied Psychology, 91,* 1359-1374. https://doi.org/10.1037/0021-9010.91.5.1359

de Lange, A. H., Taris, T. W., Kompier, M. A. J., Houtman, I. L. D., & Bongers, P. M. (2003). "The Very Best of the Millennium": Longitudinal Research and the Demand-Control-(Support) Model. *Journal of Occupational Health Psychology, 8,* 282-305. https://doi.org/10.1037/1076-8998.8.4.282

De Raeve, L., Vasse, R. M., Jansen, N. W. H., van den Brandt, P. A., & Kant, I. (2007). Mental Health Effects of Changes in Psychosocial Work Characteristics: A Prospective Cohort Study. *Journal of Occupational & Environmental Medicine, 49,* 890-899. https://doi.org/10.1097/jom.0b013e31811eadd3

Demerouti, E., Bakker, A. B., Sonnentag, S., & Fullagar, C. J. (2012). Work-Related Flow and Energy at Work and at Home: A Study on the Role of Daily Recovery. *Journal of Organizational Behavior, 33,* 276-295. https://doi.org/10.1002/job.760

Dettmers, J. (2017). How Extended Work Availability Affects Well-Being: The Mediating Roles of Psychological Detachment and Work-Family-Conflict. *Work & Stress, 31,* 24-41. https://doi.org/10.1080/02678373.2017.1298164

Dormann, C., & Griffin, M. A. (2015). Optimal Time Lags in Panel Studies. *Psychological Methods, 20,* 489-505. https://doi.org/10.1037/met0000041

Feldmann, E. (2018). *Psychische Belastungen im Arbeitskontext—Inhaltsbezogene und methodenkritische Analysen zur Weiterentwicklung des Verfahrens GPB.* https://archiv.ub.uni-heidelberg.de/volltextserver/24069/

Fila, M. (2016). The Job Demands, Control, Support Model: Where Are We Now? *TKM International Journal for Research in Management, 1,* 15-44.

Fila, M. J., Purl, J. D., & Bracken, W. (2013). "Overdue: Meta-Analyzing Demands, Control and Support on Job Satisfaction and Emotional Exhaustion. *Academy of Management Proceedings, 2013,* Article 16912. https://doi.org/10.5465/ambpp.2013.16912abstract

Fila, M. J., Purl, J., & Griffeth, R. W. (2017). Job Demands, Control and Support: Meta-Analyzing Moderator Effects of Gender, Nationality, and Occupation. *Human Resource Management Review, 27,* 39-60. https://doi.org/10.1016/j.hrmr.2016.09.004

Frese, M., & Zapf, D. (1988). Methodological Issues in the Study of Work Stress. In C. L. Cooper, & R. Payne (Eds.), Causes, Coping and Consequences of Stress at Work (pp. 375-411). Wiley.

Garst, H., Frese, M., & Molenaar, P. C. M. (2000). The Temporal Factor of Change in Stressor-Strain Relationships: A Growth Curve Model on a Longitudinal Study in East Germany. *Journal of Applied Psychology, 85,* 417-438. https://doi.org/10.1037//0021-9010.85.3.417

Gould, S. (1979). An Equity—Exchange Model of Organizational Involvement. *Academy of Management Review, 4,* 53-62. https://doi.org/10.5465/amr.1979.4289183

Halbesleben, J. R. B., & Demerouti, E. (2005). The Construct Validity of an Alternative

Measure of Burnout: Investigating the English Translation of the Oldenburg Burnout Inventory. *Work & Stress, 19,* 208-220. https://doi.org/10.1080/02678370500340728

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 & Stress, 24,* 1-35. https://doi.org/10.1080/02678371003683747

Holmgreen, L., Tirone, V., Gerhart, J., & Hobfoll, S. E. (2017). Conservation of Re-sources Theory. In C. L. Cooper, & J. C. Quick (Eds.), *The Handbook of Stress and Health* (pp. 443-457). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118993811.ch27

Huang, Y., Du, P., Chen, C., Yang, C., & Huang, I. (2011). Mediating Effects of Emotional Exhaustion on the Relationship between Job Demand-Control Model and Mental Health. *Stress and Health, 27,* e94-e109. https://doi.org/10.1002/smi.1340

IBM Corp (2022). IBM SPSS Statistics for Windows (29).

JAMOVI (2022). The Jamovi Project (2.3).

Jansen, N. W. H. (2003). *Working Time Arrangements, Work-Family Conflict, and Fatigue.* Master's Thesis, Maastricht university. https://doi.org/10.26481/dis.20031219nj

Johnson, J. V., & Hall, E. M. (1988). Job Strain, Work Place Social Support, and Cardiovascular Disease: A Cross-Sectional Study of a Random Sample of the Swedish Working Population. *American Journal of Public Health, 78,* 1336-1342. https://doi.org/10.2105/ajph.78.10.1336

Jonge, J., & Dormann, C. (2003). The DISC Modell: Demand-Induced Strain Compensation Mechanisms in Job Stress. In M. Dollard, H. R. Winefield, & A. H. Winefield (Eds.), *Occupational Stress in the Service Professions* (pp. 43-74). CRC Press. https://doi.org/10.1201/9780203422809.ch2

Kain, J., & Jex, S. (2010). Karasek's (1979) Job Demands-Control Model: A Summary of Current Issues and Recommendations for Future Research. In P. L. Perrewé & D. C. Ganster (Eds.), *New Developments in Theoretical and Conceptual Approaches to Job Stress* (pp. 237-268). Emerald Group Publishing Limited. https://doi.org/10.1108/s1479-3555(2010)0000008009

Karasek, R. A. (1979). Job Demands, Job Decision Latitude, and Mental Strain: Implications for Job Redesign. *Administrative Science Quarterly, 24,* 285-308. https://doi.org/10.2307/2392498

Kubicek, B., Korunka, C., & Tement, S. (2014). Too Much Job Control? Two Studies on Curvilinear Relations between Job Control and Eldercare Workers' Well-being. *International Journal of Nursing Studies, 51,* 1644-1653. https://doi.org/10.1016/j.ijnurstu.2014.05.005

Lazarus, R. S., & Folkman, S. (1984). *Stress, Appraisal, and Coping.* Springer Publishing Company.

Lesener, T., Gusy, B., & Wolter, C. (2019). The Job Demands-Resources Model: A Meta-Analytic Review of Longitudinal Studies. *Work & Stress, 33,* 76-103. https://doi.org/10.1080/02678373.2018.1529065

Lichtenthaler, P. W., & Fischbach, A. (2016). Job Crafting and Motivation to Continue Working Beyond Retirement Age. *Career Development International, 21,* 477-497. https://doi.org/10.1108/cdi-01-2016-0009

Machin, M. A., & Hoare, P. N. (2008). The Role of Workload and Driver Coping Styles in Predicting Bus Drivers' Need for Recovery, Positive and Negative Affect, and Physical Symptoms. *Anxiety, Stress & Coping, 21,* 359-375. https://doi.org/10.1080/10615800701766049

Maslach, C. (1998). A Multidimensional Theory of Burnout. In C. L. Cooper (Ed.), *Theories of Organizational Stress* (pp. 68-85). Oxford University Press Oxford. https://doi.org/10.1093/oso/9780198522799.003.0004

Maslach, C., Jackson, S. E., & Leiter, M. P. (1997). Maslach Burnout Inventory: Third Edition. In C. P. Zalaquett, & R. J. Wood (Eds.), *Evaluating STRESS: A book of Resources* (pp. 91-218). Scarecrow Education.

Melamed, S., Ben-Avi, I., Luz, J., & Green, M. S. (1995). Objective and Subjective Work Monotony: Effects on Job Satisfaction, Psychological Distress, and Absenteeism in Blue-Collar Workers. *Journal of Applied Psychology, 80,* 29-42. https://doi.org/10.1037/0021-9010.80.1.29

Microsoft (2019). Microsoft Excel (365).

Podsakoff, N. P., LePine, J. A., & LePine, M. A. (2007). Differential Challenge Stressor-Hindrance Stressor Relationships with Job Attitudes, Turnover Intentions, Turnover, and Withdrawal Behavior: A Meta-Analysis. *Journal of Applied Psychology, 92,* 438-454. https://doi.org/10.1037/0021-9010.92.2.438

Reyes, M. L., & Lee, J. D. (2008). Effects of Cognitive Load Presence and Duration on Driver Eye Movements and Event Detection Performance. *Transportation Research Part F: Traffic Psychology and Behaviour, 11,* 391-402. https://doi.org/10.1016/j.trf.2008.03.004

Simbula, S., Mazzetti, G., & Guglielmi, D. (2019). A Three-Wave Study on the Reciprocal Relationships between Emotional Dissonance, Need for Recovery, and Exhaustion. *Sustainability, 11,* Article 5183. https://doi.org/10.3390/su11195183

Sonnentag, S., & Bayer, U. (2005). Switching off Mentally: Predictors and Consequences of Psychological Detachment from Work during Off-Job Time. *Journal of Occupational Health Psychology, 10,* 393-414. https://doi.org/10.1037/1076-8998.10.4.393

Sonnentag, S., & Fritz, C. (2007). The Recovery Experience Questionnaire: Development and Validation of a Measure for Assessing Recuperation and Unwinding from Work. *Journal of Occupational Health Psychology, 12,* 204-221. https://doi.org/10.1037/1076-8998.12.3.204

Sonnentag, S., & Fritz, C. (2015). Recovery from Job Stress: The Stressor-Detachment Model as an Integrative Framework. *Journal of Organizational Behavior, 36,* S72-S103. https://doi.org/10.1002/job.1924

Sonnentag, S., & Zijlstra, F. R. H. (2006). Job Characteristics and Off-Job Activities as Predictors of Need for Recovery, Well-Being, and Fatigue. *Journal of Applied Psychology, 91,* 330-350. https://doi.org/10.1037/0021-9010.91.2.330

Sonntag, K., & Feldmann, E. (2022). Gefährdungsbeurteilung psychischer Belastung im Arbeitskontext und nachfolgende Maßnahmen. In A. Michel, & A. Hoppe, (Eds.), *Handbuch Gesundheitsförderung bei der Arbeit* (pp. 149-163). Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-28651-4_15

Spector, P. E. (2006). Method Variance in Organizational Research. *Organizational Research Methods, 9,* 221-232. https://doi.org/10.1177/1094428105284955

Stab, N., Hacker, W., & Weigl, M. (2016). Work Organization in Hospital Wards and Nurses' Emotional Exhaustion: A Multi-Method Study of Observation-Based Assessment and Nurses' Self-Reports. *International Journal of Nursing Studies, 61,* 52-62. https://doi.org/10.1016/j.ijnurstu.2016.05.012

Stevens, M. L., Crowley, P., Garde, A. H., Mortensen, O. S., Nygård, C., & Holtermann, A. (2019). Validation of a Short-Form Version of the Danish Need for Recovery Scale against the Full Scale. *International Journal of Environmental Research and Public Health, 16,* Article 2334. https://doi.org/10.3390/ijerph16132334

Ullman, J. B., & Bentler, P. M. (2012). Structural Equation Modeling. In J. A. Schinka, W. F. Velicer, & I. B. Weiner (Eds.), *Handbook of Psychology, Second Edition* (pp. 661-690). John Wiley & Sons, Inc. https://doi.org/10.1002/9781118133880.hop202023

Van der Doef, M., & Maes, S. (1999). The Job Demand-Control (-Support) Model and Psychological Well-Being: A Review of 20 Years of Empirical Research. *Work & Stress, 13,* 87-114. https://doi.org/10.1080/026783799296084

van Dick, R., Wagner, U., Stellmacher, J., & Christ, O. (2005). Mehrebenenanalysen in der Organisationspsychologie: Ein Plädoyer und ein Beispiel. *Zeitschrift für Arbeits- und Organisationspsychologie A&O, 49,* 27-34. https://doi.org/10.1026/0932-4089.49.1.27

van Vegchel, N., de Jonge, J., & Landsbergis, P. A. (2005). Occupational Stress in (inter)action: The Interplay between Job Demands and Job Resources. *Journal of Organizational Behavior, 26,* 535-560. https://doi.org/10.1002/job.327

Veldhoven, M. (2008). Need for Recovery after Work: An Overview of Construct, Measurement and Research. In S. L. Houdmont, (Ed.), *Occupational Health Psychology European Perspectives on Research, Education and Practice* (pp. 1-25). Nottingham University Press.

Ward, N., Hussey, E. K., Cunningham, E. C., Paul, E. J., McWilliams, T., & Kramer, A. F. (2019). Building the Multitasking Brain: An Integrated Perspective on Functional Brain Activation during Task-Switching and Dual-Tasking. *Neuropsychologia, 132,* Article ID: 107149. https://doi.org/10.1016/j.neuropsychologia.2019.107149

Ward, S., & Steptoe-Warren, G. (2013). A Conservation of Resources Approach to Blackberry Use, Work-Family Conflict and Well-Being: Job Control and Psychological Detachment from Work as Potential Mediators. *Engineering Management Research, 3,* 8-23. https://doi.org/10.5539/emr.v3n1p8

Watson, D., & Clark, L. A. (1984). Negative Affectivity: The Disposition to Experience Aversive Emotional States. *Psychological Bulletin, 96,* 465-490. https://doi.org/10.1037//0033-2909.96.3.465

Watson, D., Pennebaker, J. W., & Folger, R. (1987). Beyond Negative Affectivity. *Journal of Organizational Behavior Management, 8,* 141-158. https://doi.org/10.1300/j075v08n02_09