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RESEARCH REPORT

Do Interactions Matter? Assessing the Role of Job Characteristics Interactions on Employee Well-Being

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The job demands–resources model suggests that job demands (e.g., workload) and resources (e.g., autonomy) relate to employee well-being through both main and interactive effects. Although the predictive validity of main effects is well established, the validity of the proposed interaction effects, buffering and boosting, remains unclear. Prior research has examined only selected combinations of job characteristics, leaving open the possibility that unexplored interactions may still be informative. In this study, we conducted a comprehensive analysis of 24 job characteristics and all possible nonlinear and higher order interactions among them using machine learning methods in a large, quota-representative sample of the German working population (N = 100,000) stratified by industry, gender, age, and employment status. We compared the out-of-sample predictive performance of models capturing main effects (linear mixed-effects models) with models capable of modeling complex interactions (boosting algorithms). The inclusion of interaction effects did not improve predictive accuracy beyond models based solely on main effects. These findings challenge the validity of buffer and boost effects as global mechanisms across jobs and organizations, as interactions among job characteristics did not meaningfully contribute to predicting either burnout or work engagement. Instead, job characteristics appear to exert only additive effects.

Keywords: employee well-being, job demands, job resources, interactions, machine learning

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The job demands–resources model (JD-R; Demerouti et al., 2001) is one of the most influential frameworks for understanding how job characteristics relate to employee well-being. It distinguishes between demands (e.g., workload) and resources (e.g., autonomy), which show consistent, well-supported main effects on strain and motivation (e.g., Alarcon, 2011; Christian et al., 2011; Crawford et al., 2010; Guthier et al., 2020; Halbesleben, 2010; Knight et al., 2017; Lesener et al., 2020; Mazzetti et al., 2023). Beyond their main effects, JD-R proposes two theoretically important demand–resource interaction effects. The buffer effect concerns strain: The positive association between demands and burnout is expected to be weaker when resources are high (i.e., resources are expected to buffer the effect of demands on burnout). The boost effect concerns motivation: The positive association between resources and work engagement is expected to be stronger when demands are high (i.e., demands are expected to strengthen the motivating effect of resources on work engagement). Statistically, both correspond to a single Demand × Resource interaction: on burnout for buffering and on work engagement for boosting. They are therefore distinct from, and additional to, the well-established main effects of demands and resources (Bakker et al., 2023). Two recent meta-analyses (Gonzalez-Mulé et al., 2021; Huth & Chung-Yan, 2023) suggest the buffer effect is weak or false, directly challenging a core interaction mechanism on which the JD-R and its predecessor models were built. Moreover, the evidence base regarding boost effects is even thinner, underscoring the need for more comprehensive tests of both interaction processes.

To move the field forward, it is necessary to test JD-R's interaction claims across a broader set of job characteristics and with methods capable of modeling nonlinear complexities. Huth and Chung-Yan's (2023) work leaves suggestions for future research, which became the focus of the present work: expanding the range of job characteristics examined beyond the limited set they were able to study meta-analytically and testing potential nonlinear relationships. These directions align with broader calls for more comprehensive approaches to modeling the psychosocial work environment (Elovainio et al., 2022; Parker et al., 2017). Yet progress toward these goals has been historically constrained by small samples and reliance on traditional regression models, which limit the capacity to test high-dimensional interactions and increase the risk of overfitting.

To address this gap, the present study uses supervised machine learning techniques to model high-complexity nonlinear interactions in a quota sample of 100,000 workers from the German working population across a comprehensive set of 24 job characteristics using the Copenhagen Psychosocial Questionnaire (COPSOQ). Most centrally, this design enables a more meaningful and comprehensive test of JD-R's proposed interactions between job characteristics that provide predictive value beyond additive main effects and follows Yarkoni and Westfall's (2017) recommendations to examine predictive utility as a critical test of theory. Importantly, we aim to examine whether interaction effects contribute meaningfully to prediction across jobs and organizations overall, rather than within isolated subgroups. This expands upon and directly addresses the concerns outlined by Huth and Chung-Yan (2023). We additionally employ state-of-the-art cross-validation techniques for machine learning research to ensure robustness and to evaluate generalizability.

In the remainder of the present article, we (a) review empirical evidence supporting the main effects of job characteristics on well-being, (b) discuss the mixed evidence on interaction effects, and (c) elaborate on how machine learning helps overcome these limitations. With this foundation, we empirically compare the performance of main effects models versus interaction models in predicting employee well-being and discuss implications for JD-R and practice in applied psychology.

Main Effects of Job Characteristics on Employee Well-Being

JD-R incorporates a wider array of both job demands, defined as physical, psychological, social, or organizational factors requiring sustained effort, and job resources, defined as aspects of the job that promote motivation, support goal achievement, and foster personal development (Bakker et al., 2023). The model presents two distinct processes explaining employee well-being: (a) a health impairment process, where excessive job demands deplete employees' resources, leading to strain, exhaustion, and health problems (Bakker et al., 2023), and (b) a motivational process, where job resources enhance employee engagement, creativity, and performance by meeting basic psychological needs (e.g., Bakker & Xanthopoulou, 2013). In foundational JD-R studies, strain is typically captured via burnout and motivation via work engagement (e.g., Bakker & Demerouti, 2007; Bakker et al., 2023; Demerouti & Bakker, 2023).

The models' main effects are supported by extensive literature and meta-analyses, consistently linking burnout to challenge and hindrance demands, role ambiguity, role conflict, workload, and work pressure (Alarcon, 2011; Crawford et al., 2010; Lee & Ashforth, 1996); workload intensity, job insecurity, emotional demands, and role stressors (Aronsson et al., 2017; Guthier et al., 2020); and physical workload, time pressure, and shift work (Demerouti et al., 2001). Work engagement is linked to job resources such as autonomy, job control, role clarity, social resources, leadership, and development opportunities (Alarcon, 2011; Lesener et al., 2020; Mazzetti et al., 2023) with antecedents including social support, feedback, and task significance (Christian et al., 2011). Other studies highlight the role of feedback, rewards, job security, and supervisor support, underscoring the importance of organizational and managerial support for workplace motivation (Demerouti et al., 2001).

Building on the literature that outlines the main effects of job characteristics on employee well-being, it is crucial to first assess the extent to which these direct effects predict variations in burnout and work engagement as pathways of employee well-being. Understanding their predictive power provides a baseline for evaluating whether additional complexities, such as interactions or nonlinearities, enhance predictive accuracy. Moreover, identifying which job characteristics are most strongly associated with employee well-being enables a more focused assessment of their relative predictive relevance. By comparing the importance of individual predictors, we can determine not only whether main effects are sufficient but also which (groups of) characteristics offer the greatest predictive utility. This leads to our first two research questions (RQs):

> *RQ1:* To what extent do individual job characteristics (i.e., main effects) predict variation in (a) burnout and (b) work engagement?

RQ2: Which job characteristics are most important for predicting employee (a) burnout and (b) work engagement?

Mixed Evidence on Buffer and Boost Effects

Within the JD-R framework, interactions between job characteristics are conceptualized as multiplicative effects between demands and resources (Bakker et al., 2023) and typically tested as statistical interactions (e.g., Bakker et al., 2005; Van Woerkom et al., 2016; Xanthopoulou et al., 2007). The framework specifies two categories of interaction effects: the buffer effect, where job resources mitigate the negative impact of demands on burnout, and the boost effect, where demands amplify the positive influence of resources on work engagement. Figure 1 illustrates the JD-R framework, incorporating our COPSOQ study variables, and shows how job resources are theorized to buffer the negative effects of demands on burnout and boost the positive effects of resources on work engagement.

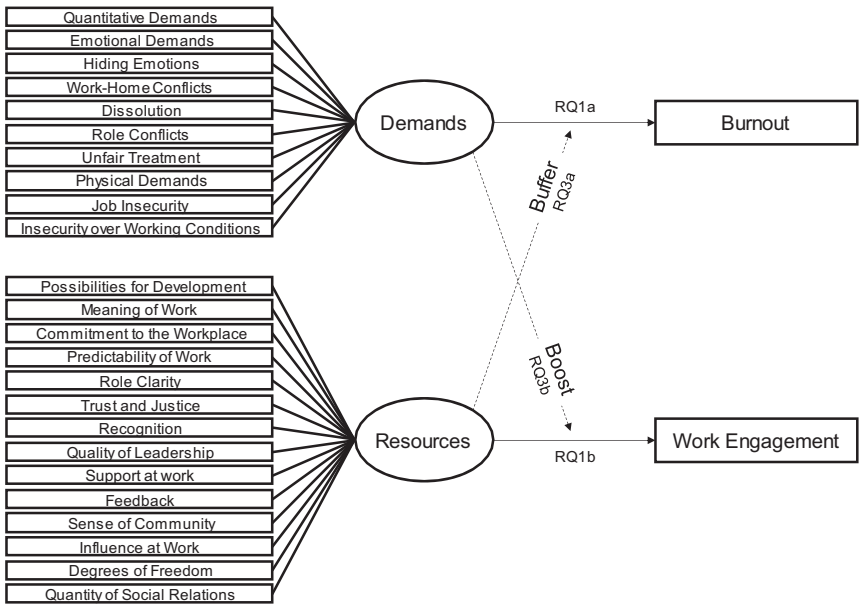
As outlined by Bakker et al. (2005), the buffer effect operates when resources help employees to (a) predict demands (e.g., role clarity enabling anticipation of when and how demands will occur), (b) understand demands (e.g., supervisor information clarifying why demands exist and their broader context), and (c) control demands (e.g., autonomy providing discretion in how to respond). Empirical studies confirm this assumption, showing that autonomy, feedback, social support, and recovery opportunities buffer the adverse effects of workload, emotional demands, or role conflict on well-being (Bakker et al., 2005; De Jonge & Huter, 2021; Lavoie-Tremblay et al., 2014; Tadić et al., 2015). Importantly, JD-R does not prescribe a specific set of buffering resources, suggesting that any demand or resource relevant to a given job may play a role.

In contrast, the boost effect occurs when demands (a) increase the value of resources, making their usefulness more apparent in challenging situations (e.g., autonomy or social support); (b) activate resources, prompting employees to deliberately engage with them (e.g., seeking feedback or drawing on support); and (c) create opportunities for growth, such as learning, mastery, and development supported by resources (Demerouti & Bakker, 2023). Empirical findings show that challenge demands such as workload and work complexity are associated with stronger motivational effects of resources like autonomy, feedback, training, social support, and intellectual stimulation (Bakker et al., 2007; Breevaart & Bakker, 2018; Hakanen et al., 2017).

Despite evidence from individual studies, two recent meta-analyses provide strong evidence against meaningful interactions between job characteristics. Huth and Chung-Yan (2023) conducted a Bayesian meta-analysis of 104 effect sizes and 14 participant-level data sets, finding that job control does not buffer the effects of demands on well-being. Their data were over 6,000 times more likely to support the absence of an interaction than its presence, a result consistent across cross-sectional and longitudinal studies as well as models assuming nonlinear effects. This challenged key assumptions of the demand–control model (Karasek, 1979) and

Figure 1

Theoretical Relationships Between Study Variables According to the Job–Demands Resources Model



Note. Ovals should not be interpreted to imply demands and resources are latent; instead, any or all individual demands and their interactions predict burnout, any or all individual resources and their interactions predict work engagement, and any or all individual demands interact with all possible resources to predict burnout (buffering) or work engagement (boosting). RQ = research question. The general idea of the figure is taken from Bakker and Demerouti (2007).

JD-R that autonomy or control buffers high workload demands. Similarly, Gonzalez-Mulé et al. (2021) analyzed 77 samples with over 140,000 participants and found weak and inconsistent evidence for interactions between demands and control or social support, suggesting that buffer effects are minimal or absent. Instead, they reported stronger support for additive main effect models, where demands, control, and social support contribute independently to employee well-being.

Although both meta-analyses arrive at the same overarching conclusion that widely assumed interaction effects within organizational stress models lack strong empirical support, they differ in scope: Huth and Chung-Yan (2023) examined only job control as a moderator, while Gonzalez-Mulé et al. (2021) considered both job control and social support within broader stress models. Yet both reviews were limited by their focus on a narrow set of characteristics and simple two-way interactions. Open questions remain about potential interactions of other job characteristics and higher order interactions, including whether combinations of resources jointly influence how demands are experienced and how factors such as role clarity, leadership, and self-efficacy interact with demands to predict well-being. Research on psychosocial work environments suggests these dynamics are more complex, often unfolding through moderating, mediating, or cumulative pathways (Bakker et al., 2010; Geisler et al., 2019; Teetzen et al., 2023). Furthermore, while the buffer effect has been extensively scrutinized, far less is known about the boost effect, raising questions about when, and for whom, demands may strengthen the motivational role of resources. As a result, although the meta-analytic evidence questions the existence of many two-way buffer effects, it leaves open whether more complex or synergistic interactions might still offer explanatory or predictive value.

To address this gap, we investigate whether accounting for interactions across the full set of job characteristics improves the prediction of employee well-being beyond additive main effects. Furthermore, we assess which specific interactions contribute most strongly to predictive performance. This leads to our third and fourth RQs:

> *RQ3:* To what extent do interactions between job characteristics support the theoretical propositions of (a) buffering effects on burnout and (b) boosting effects on work engagement?
>
> *RQ4:* Which interactions between job characteristics are most important for predicting employee well-being?

Theoretical Importance of Machine Learning

A major challenge for previous researchers in testing theories about complex interactions like those proposed in the JD-R framework lies in the limitations of the general linear model. The regression methods commonly applied in the organizational sciences are ill-equipped to address the complexity and scale of such RQs. Most critically, these methods are vulnerable to overfitting, a methodological issue in which data set-specific variation rather than true, underlying effects are parameterized in the model, leading to low-generalization performance on unseen data (Hawkins, 2004). In the context of the psychosocial work environment, the sheer number of possible interactions among all job characteristics exacerbates this issue. In the present study's 24 variables, the total number of effects that can be modeled is 24 main effects and 16,777,191 interactions (calculated as $2^{24} - 1 - 24$, representing the total number of possible subsets of 24 variables, excluding the empty set and main effects). Of these interactions, 2,300 occur in two- and three-way interactions alone, with 276 two-way interactions and 2,024 three-way interactions. This makes it practically impossible for traditional approaches to capture the full scope of these relationships with Neyman–Pearson null-hypothesis testing.

Modern machine learning methods were developed in part to overcome this class of limitation by sacrificing the unbiased measurement of population values of individual coefficients in exchange for maximizing out-of-sample predictive accuracy. Optimization of this bias–variance trade-off enables such methods to maximize predictive accuracy while still incorporating myriad, high-complexity interactions as long as sample size is sufficiently large (Pargent et al., 2023; Yarkoni & Westfall, 2017). Although machine learning models often do not provide directly interpretable coefficients as in traditional linear regression, they do offer established interpretation methods that allow researchers to understand feature contributions. Beyond individual feature importances, differences between models in overall predictive accuracy can be informative to theory. This capability positions machine learning as a transformative tool for uncovering the nuanced dynamics of demands, resources, and well-being. Modern machine learning methods accomplish this by employing techniques such as k-fold cross-validation and regularization to improve predictive accuracy and generalizability. Cross-validation repeatedly optimizes and tests models on different data subsets, while regularization penalizes overly complex solutions, reducing the influence of irrelevant or collinear predictors. These and other optimizations allow machine learning models to remain robust even in high-dimensional data sets, a common challenge when simultaneously considering many job characteristics.

A further advantage of machine learning lies in its ability to automatically identify nonlinear relationships and interactions that generalize out-of-sample. In contrast, traditional regression requires researchers to prespecify such interactions (e.g., additive, multiplicative, or ratio terms; Van Vegchel et al., 2005), an approach that is inherently limited when the number of possible combinations is large. Traditional regression represents interactions through algebraic coefficients within a single linear equation, such that correlated interaction terms may offset one another under multicollinearity. By contrast, tree-based machine learning models encode interactions structurally through recursive partitioning of the predictor space rather than through single global interaction parameters. This reduces reliance on prespecified functional forms and avoids mechanical coefficient offsetting typical of linear models. By automatically detecting complex dynamics between demands and resources within a cross-validated predictive framework, machine learning provides a flexible approach to capturing the multifaceted structure of job characteristics and their links to employee well-being. This capacity reduces dependence on strong parametric assumptions and facilitates large-scale evaluation of JD-R propositions.

Method

Participants

The data stem from employee surveys conducted primarily to meet legal requirements for psychosocial risk assessments, administered by

the Freiburg Research Center for Occupational Sciences (FFAW) GmbH on behalf of client organizations. Organizations were not subject to inclusion or exclusion criteria, ensuring a broad and diverse pool of employers. A quota-representative sample of the German workforce was drawn to match national distributions of age, gender, employment status, and occupation (see Table 1). From this pool, a random sample of 100,000 employees across 888 organizations was selected, with an average of 112.6 participants per organization (SD = 220.1, range = 1–3,347). Data were collected between 2017 and 2021. The study was approved by the ethical committee of the Leibniz Research Centre for Working Environment and Human Factors (ID 249).

Measures

Job Characteristics

The COPSOQ was designed to measure job characteristics and their effects on employee well-being comprehensively. Originally developed in Denmark (Kristensen et al., 2005), the COPSOQ has been widely adopted worldwide and featured in over 400 peer-reviewed studies on work and health (Burr et al., 2019; Nolle & Haeberle, 2022). In Germany, the first version was validated by Nübling et al. (2006), with the most recent third version being validated by Lincke et al. (2021). This version assesses 24 job characteristics (for an overview, see Table 2), which we divided into demands or resources based on the theoretical definitions of Bakker et al. (2023). More detailed descriptions of these job characteristics are available in Burr et al. (2019).

Employee Well-Being

We followed established practice in the JD-R literature by operationalizing strain and motivation through burnout and work engagement, consistent with prior work (see Bakker & Demerouti, 2007; Bakker et al., 2023; Demerouti & Bakker, 2023), measured as burnout symptoms and work engagement in COPSOQ (Burr et al., 2019; Lincke et al., 2021).

Analytical Strategy

Model Performance

Several supervised machine learning models, such as Random Forests and XGBoost, are well-suited for prediction tasks and can model high-dimensional interactions (see Pargent et al., 2023). However, these approaches have limitations with nested data, such as employees grouped within organizations. Employees in the same organization often share features like culture, management style, or policies, meaning their observations are not independent. Ignoring this hierarchical structure can bias results, as many machine learning models, like traditional regression, assume independence (Hox et al., 2017). To address this limitation, we used GPBoost (Sigrist, 2022, 2023), which integrates gradient boosting with linear mixed models. Linear mixed models explicitly model hierarchical structures by incorporating both fixed and random effects. Further details on GPBoost are provided in the Supplemental Material SI-3.

We used the GPBoost library in R (Sigrist, 2024) to build main-effect and interaction-effect models. Prediction performance was evaluated using fivefold cross-validation, a standard machine

Table 1
Comparison of Demographics Between Our Sample and the German Working Population

Descriptive	Our sample	Population
Gender		
Male	50.5%	52.1%
Female	49.3%	47.9%
Other	0.2%	
Age		
<25 years	5.9%	10.3%
25–34 years	23.1%	21.4%
35–44 years	24.4%	20.8%
45–54 years	28.6%	25.7%
55+ years	18.0%	21.7%
Employment status		
Full-time	74.0%	64.3%
Part-time	26.0%	35.7%
Occupation		
Agriculture, forestry, farming, and gardening	0.6%	1.5%
Production of raw materials and goods and manufacturing	18.6%	20.1%
Construction, architecture, surveying, and technical building services	4.1%	5.6%
Natural sciences, geography, and informatics	5.8%	3.9%
Traffic, logistics, safety, and security	9.6%	14.0%
Commercial services, trading, sales, the hotel business, and tourism	12.7%	12.0%
Business organization, accounting, law, and administration	23.8%	21.0%
Health care, the social sector, teaching, and education	21.8%	19.3%
Philology, literature, humanities, social sciences, economics, media, art, culture, and design	3.0%	2.5%

Note. Demographics for the German working population were derived from the Federal Statistical Office of Germany; they only report male and female statistics.

Table 2
Overview of All COPSOQ Variables With Sample Items

Dimension	Sample item	Theoretical rationale for mapping
Demands		
Quantitative demands	Do you have to work very fast?	Working very fast requires sustained cognitive and physical effort.
Emotional demands	Is your work emotionally demanding?	Emotionally demanding work requires sustained emotional effort.
Hiding emotions	Does your work require that you hide your feelings?	Suppressing feelings requires continuous emotional effort.
Work–home conflicts	The demands of my work interfere with my private and family life.	Work interfering with private life increases psychological effort and strain.
Dissolution	I take care of work-related tasks outside of my working time as well.	Doing work tasks outside work hours requires additional sustained effort.
Role conflicts	Are contradictory demands placed on you at work?	Contradictory demands require extra cognitive effort to manage incompatible requirements.
Unfair treatment	How often do you feel unjustly criticized, bullied, or shown up in front of others by your colleagues and your superior?	Experiencing unjust criticism or bullying increases emotional effort to cope with it.
Physical demands	How often do you have to do physically strenuous work such as lift, carry, or raise heavy objects?	Strenuous physical work requires sustained physical effort.
Job insecurity	Are you worried about becoming unemployed?	Worry about unemployment creates ongoing psychological effort.
Insecurity over working conditions	Are you worried about the timetable being changed (e.g., shift, weekdays, time to enter and leave) against your will?	Uncertainty about shifts or schedules forces continuous cognitive and emotional effort.
Resources		
Possibilities for development	Do you have the possibility of learning new things through your work?	Learning opportunities support personal growth and help achieve work goals.
Meaning of work	Do you feel that the work you do is important?	Feeling that work is important provides motivation and supports the achievement of goals.
Commitment to workplace	Are you proud of being part of this organization?	Pride in the organization strengthens motivation and contributes to positive functioning.
Predictability of work	Do you receive all the information you need in order to do your work well?	Receiving necessary information supports effective work performance and helps to anticipate demands.
Role clarity	Do you know exactly which areas are your responsibility?	Knowing responsibilities helps achieve work goals and reduces the negative effects of demands.
Trust and justice	Can the employees trust the information that comes from the management?	Reliable information from management provides psychological support and helps maintain motivation.
Recognition	Is your work recognized and appreciated by the management?	Appreciation supports motivation and helps employees feel that their efforts contribute to goals.
Quality of leadership	To what extent would you say that your immediate superior gives high priority to job satisfaction?	Leadership that prioritizes well-being offers organizational support that helps meet work goals.
Support at work	How often do you get help and support from your colleagues, if needed?	Help from colleagues is a social resource that supports goal achievement.
Feedback	How often does your immediate superior talk with you about how well you carry out your work?	Performance discussions guide improvement, supporting learning and the achievement of work goals.
Sense of community	Is there a good atmosphere between you and your colleagues?	A positive atmosphere provides social support.
Influence at work	Do you have a large degree of influence on the decisions concerning your work?	Having influence increases autonomy, which supports motivation and helps achieve work goals.
Degrees of freedom (breaks/holidays)	Can you take holidays more or less when you wish?	Flexibility in rest periods helps regulate the strain caused by demands and supports recovery.
Quantity of social relations	Is it possible for you to talk to your colleagues while you are working?	Being able to talk with colleagues provides social resources that support coping and goal achievement.
Burnout		
Burnout symptoms	How often do you feel emotionally exhausted?	
Work engagement		
Work engagement	At my work, I am full of energy.	

Note. We classified COPSOQ job characteristics as either demands or resources according to the definitions provided by Bakker et al. (2023). COPSOQ = Copenhagen Psychosocial Questionnaire.

learning approach that improves robustness and reduces overfitting. Performance metrics included root mean square error, mean absolute error, Spearman's ρ, and R^2, each calculated on the test data of every fold. Missing values were median-imputed within folds, given the low overall missingness (on average 2.7% per job characteristic). For the interaction models, we used nested resampling with a fivefold outer loop for performance evaluation and an 80/20 holdout split in the inner loop for hyperparameter tuning. This prevents information leakage by ensuring model selection (e.g., hyperparameter tuning) and evaluation occur on separate

subsets, yielding more reliable generalization estimates (Pargent et al., 2023). Hyperparameters were tuned via random search, drawing 100 parameter combinations from the grid. Each model was trained for up to 10,000 rounds, with early stopping after 10 rounds without improvement, and the best parameters were then evaluated on the test set using the standardized metrics.

Model Interpretation

To interpret the prediction models, we used SHapley Additive exPlanations (SHAP) values (Lundberg & Lee, 2017), a model-agnostic method that attributes predictions to input features based on cooperative game theory. Each SHAP value represents the marginal contribution of a job characteristic to a given prediction, averaged across all possible subsets of features in which it might appear. This provides a fair and consistent decomposition of model output, even for complex, nonlinear models such as GPBoost. For each observation, the prediction equals the sum of the SHAP values plus a baseline (the mean prediction). We further computed SHAP interaction values, which capture how pairs of job characteristics jointly contribute to predictions beyond their main effects. While GPBoost can represent higher order interactions, SHAP is currently limited to two-way interactions. To assess the contribution of individual job characteristics on predictive performance, we converted the model's SHAP values into approximate feature-level contributions to explained variance (Redell, 2019).

Transparency and Openness

We make all analysis code and research materials for this project available on the Open Science Framework at https://doi.org/10.17605/OSF.IO/SA6HC. The COPSOQ data cannot be shared publicly because of copyright restrictions. Researchers may request access for scientific purposes from the Freiburg Research Centre for Occupational Sciences (https://www.copsoq.de/en). The data analyzed in the present study constitute a subset of the larger COPSOQ data set that was previously used in the validation of the German version of the COPSOQ (Lincke et al., 2021). We analyzed the data using R (Version 4.4.1; R Core Team, 2022) with the packages tidyverse for general data processing (Version 2.0.0; Wickham et al., 2019), GPBoost for the main analyses (Version 1.6.5; Sigrist, 2024), as well as the packages SHAPforxgboost (Version 0.1.3; Liu & Just, 2023), treeshap (Version 0.3.1; Komisarczyk et al., 2024), shapviz (Version 0.9.4; Mayer, 2024), and shapFlex (Version 0.3.0; Redell, 2019) for the SHAP analyses. The first author used a large language model (ChatGPT) to facilitate coding and to critically review the R code and manuscript for errors. This study was not preregistered.

Results

Table 3 displays the intercorrelation matrix among all study variables. Additional details, including descriptive statistics and reliability measures, are provided in the Supplemental Material SI-1.

Main Effect Models

RQ1 was analyzed by main effect models examining the direct effect of each job characteristic on (a) burnout and (b) work engagement as indicators of employee well-being without accounting for potential interactions between job characteristics. In these models, each job characteristic is assumed to have an independent, additive effect on the outcome. As shown in Table 4, the average cross-validated performance indicated that, for burnout (RQ1a), demands alone explained 40.0% of the variance ($R^2 = .400$), whereas models including both demands and resources explained 41.7% ($R^2 = .417$) of the variance. For work engagement (RQ1b), resources alone explained 44.8% of the variance ($R^2 = .448$), and models including both resources and demands explained 46.9% ($R^2 = .469$) of the variance. This pattern aligns with the assumed JD-R pathways: Adding resources to demand-only models yielded only a small improvement in burnout prediction ($\Delta R^2 = .017$), whereas adding demands to resource-only models produced a similarly modest gain for work engagement ($\Delta R^2 = .021$).

To address RQ2, we investigated which job characteristics are most important for predicting burnout (RQ2a) and work engagement (RQ2b). We examined SHAP values from the machine learning models and computed the proportion of explained variance attributable to each job characteristic's main effects (for more details, see the Method section). SHAP values for each job characteristic are displayed in Figure 2 for burnout and in Figure 3 for work engagement. For burnout, higher work–home conflicts were by far the most important job characteristic ($R^2 = .240$), while all others, such as higher quantitative demands ($R^2 = .027$) or physical demands ($R^2 = .031$), had comparatively small contributions. For work engagement, the strongest predictors were higher commitment to the workplace ($R^2 = .177$), higher meaning of work ($R^2 = .065$), greater possibilities for development ($R^2 = .066$), and fewer work–home conflicts ($R^2 = .073$).

Interaction Effect Models

RQ3 was examined using interaction effect models that capture both nonlinear relationships and multiway interactions among all job characteristics in predicting (a) burnout and (b) work engagement.

For burnout (RQ3a), the demands-only model included only demand variables and allowed nonlinear effects as well as interactions among demands, achieving an average cross-validated performance of $R^2 = .410$ (see Table 4). The resources-only model analogously included only resources and their within-set interactions but showed substantially lower predictive performance ($R^2 = .203$). A restricted model that included both demands and resources but constrained interactions to occur only within sets, that is, Demand × Demand and Resource × Resource combinations, reached $R^2 = .424$. Finally, the both-together model, which included demands and resources and allowed the algorithm to learn all main effects and interactions, yielded the highest performance ($R^2 = .425$). Interpreting the buffer effect as cross-set interactions between demands and resources suggests only negligible incremental value ($\Delta R^2 = .001$ between the restricted and full nonlinear models), and defining the buffer effect more broadly as general nonlinearity likewise yields only a minimal improvement beyond the full linear specification ($\Delta R^2 = .008$ compared with the linear both-together model, $R^2 = .417$). Thus, both operationalizations of the buffer effect showed limited incremental predictive value.

For work engagement (RQ3b), the resources-only model included only resource variables and allowed nonlinear effects as well as

Table 3

Pearson Correlations Between Job Characteristics and Burnout and Work Engagement

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
Demands													
1. Quantitative demands	(.81)												
2. Emotional demands	.359	(.75)											
3. Hiding emotions	.346	.550	(.80)										
4. Work–home conflicts	.569	.386	.457	(.92)									
5. Dissolution	.360	.350	.226	.417	(.63)								
6. Role conflicts	.367	.297	.417	.444	.233	(.81)							
7. Unfair treatment	.169	.118	.278	.290	.081	.364	—						
8. Physical demands	.088	.099	.180	.232	.056	.251	.279	(.84)					
9. Job insecurity	.019	−.115	.084	.107	−.081	.103	.203	.184	(.74)				
10. Insecurity over working conditions	.118	.073	.219	.269	.037	.273	.303	.368	.544	(.76)			
Resources													
11. Possibilities for development	.109	.197	−.073	−.047	.210	−.143	−.229	−.205	−.251	−.247	(.77)		
12. Meaning of work	−.027	.112	−.127	−.162	.062	−.259	−.185	−.025	−.165	−.136	.477	(.85)	
13. Commitment to workplace	−.138	−.040	−.250	−.279	.073	−.324	−.247	−.147	−.127	−.210	.421	.498	(.80)
14. Predictability of work	−.210	−.109	−.299	−.306	−.053	−.454	−.320	−.224	−.168	−.287	.328	.319	.441
15. Role clarity	−.140	−.076	−.192	−.233	−.084	−.348	−.234	−.030	−.093	−.154	.233	.421	.343
16. Trust and justice	−.238	−.142	−.314	−.353	−.059	−.493	−.384	−.237	−.189	−.318	.317	.348	.491
17. Recognition	−.161	−.073	−.261	−.277	.009	−.368	−.314	−.218	−.182	−.287	.337	.303	.464
18. Quality of leadership	−.193	−.094	−.281	−.309	−.037	−.406	−.402	−.218	−.152	−.249	.352	.302	.448
19. Support at work	−.188	−.091	−.263	−.305	−.060	−.337	−.428	−.226	−.192	−.269	.315	.262	.372
20. Feedback	−.051	.001	−.141	−.136	.033	−.139	−.152	−.061	−.068	−.088	.259	.205	.308
21. Sense of community	−.102	−.095	−.213	−.220	−.019	−.228	−.382	−.196	−.134	−.193	.236	.203	.284
22. Influence at work	−.045	.117	−.163	−.133	.163	−.164	−.222	−.202	−.214	−.255	.468	.267	.309
23. Degrees of freedom	−.126	−.202	−.229	−.259	−.160	−.178	−.200	−.363	−.083	−.262	.204	.030	.136
24. Quantity of social relations	−.144	−.096	−.161	−.158	−.048	−.052	−.100	−.070	−.075	−.105	.124	.052	.155
Outcomes													
25. Burnout	.410	.306	.396	.584	.208	.393	.309	.268	.184	.293	−.164	−.184	−.301
26. Work engagement	−.092	.002	−.208	−.291	.057	−.317	−.231	−.098	−.138	−.184	.458	.515	.570

Variable	14	15	16	17	18	19	20	21	22	23	24	25	26
14. Predictability of work	(.75)												
15. Role clarity	.506	(.81)											
16. Trust and justice	.591	.445	(.81)										
17. Recognition	.515	.347	.637	—									
18. Quality of leadership	.586	.407	.596	.547	(.91)								
19. Support at work	.459	.336	.505	.416	.630	(.83)							
20. Feedback	.337	.265	.305	.392	.446	.433	(.58)						
21. Sense of community	.282	.244	.351	.257	.327	.492	.299	(.84)					
22. Influence at work	.325	.179	.281	.317	.299	.253	.223	.164	(.76)				
23. Degrees of freedom	.185	.078	.169	.142	.182	.227	.098	.169	.299	(.59)			
24. Quantity of social relations	.126	.065	.131	.110	.128	.260	.208	.250	.162	.275	—		
Outcomes													
25. Burnout	−.313	−.229	−.347	−.308	−.307	−.287	−.166	−.248	−.194	−.227	−.152	(.84)	
26. Work engagement	.361	.377	.409	.394	.377	.303	.287	.274	.308	.095	.080	−.385	(.85)

Note. Correlations are calculated using pairwise deletion. Results based on complete data and additional COPSOQ variables are reported in the Supplemental Material SI-1. COPSOQ = Copenhagen Psychosocial Questionnaire.

interactions among resources, achieving an average cross-validated performance of $R^2 = .456$ (see Table 4). The demands-only model analogously included only demands and their interactions but showed substantially lower predictive performance ($R^2 = .210$). A restricted model that included both demands and resources but constrained interactions to occur only within sets, that is, Demand × Demand and Resource × Resource combinations, reached $R^2 = .477$. Finally, the both-together model, which included demands and resources and allowed the algorithm to learn all main effects and interactions, yielded a nearly identical performance ($R^2 = .476$). Interpreting the boost effect as cross-set interactions between demands and resources suggests no incremental value ($\Delta R^2 = -.001$ between the restricted and full nonlinear models), and defining the boost effect more broadly as general nonlinearity likewise yields only a minimal improvement beyond the full linear specification ($\Delta R^2 = .007$ compared with the linear both-together model, $R^2 = .469$). Thus, both operationalizations of the boost effect showed limited incremental predictive value.

To address RQ4 and given the limited incremental predictive value of interaction effects reported above (less than 1% of explained variance), we refrain from interpreting individual interaction patterns in isolation. When higher order effects contribute minimally to out-of-sample performance, detailed interpretation risks overstating patterns that have negligible practical relevance.

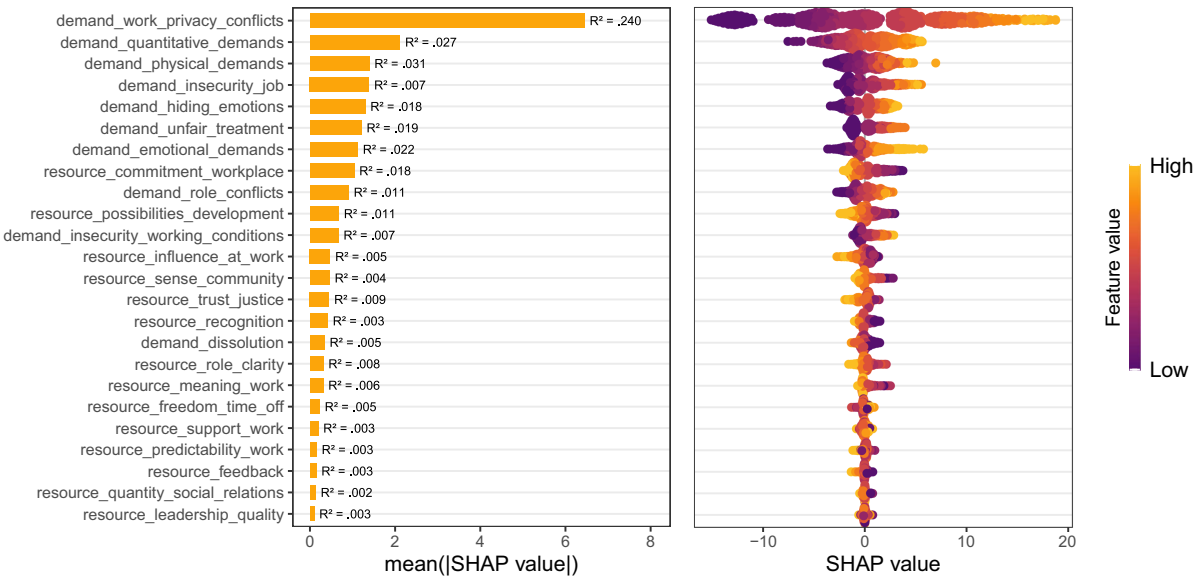
Table 4
Predictive Performance Across Models and Outcomes

Outcome	Included job characteristic	Interaction effect	R^2
Burnout	Demands	None	.400 (.024)
	Resources	None	.191 (.002)
	Demands and resources	None	.417 (.026)
	Demands	Demands only	.410 (.024)
	Resources	Resources only	.203 (.002)
	Demands and resources	Within-set only[a]	.424 (.030)
	Demands and resources	All possible	.425 (.023)
Work engagement	Resources	None	.448 (.013)
	Demands	None	.203 (.015)
	Resources and demands	None	.469 (.018)
	Resources	Resources	.456 (.014)
	Demands	Demands	.210 (.013)
	Resources and demands	Within-set only[a]	.477 (.019)
	Resources and demands	All possible	.476 (.017)

Note. R^2 values represent out-of-sample predictive performance across folds. Values are presented as the mean across resampling folds, with the standard deviation across folds in parentheses; higher values indicate better predictive performance. More performance metrics are displayed in the Supplemental Material SI-2. All models include the listed job characteristics simultaneously within each specification; results therefore do not reflect stepwise or hierarchical model building, and predictor order does not influence estimation or variable importance. Each interaction condition represents a separately estimated model in which all permitted interaction terms are learned concurrently. Differences in R^2 thus reflect differences in model specification rather than sequential inclusion of predictors or interaction terms.
[a] Within-set interactions indicate that interactions are permitted only among demand variables or among resource variables, whereas interactions between demands and resources are not estimated.

Instead, we summarize the overall interaction involvement of each job characteristic, defined as the total magnitude of its SHAP interaction values across all pairwise combinations. Across both outcomes, interaction involvement closely tracked the overall importance of predictors as reflected in mean absolute SHAP values, indicating that interaction effects largely reflect the influence of already dominant job characteristics rather than qualitatively distinct patterns. Detailed rankings of all variables

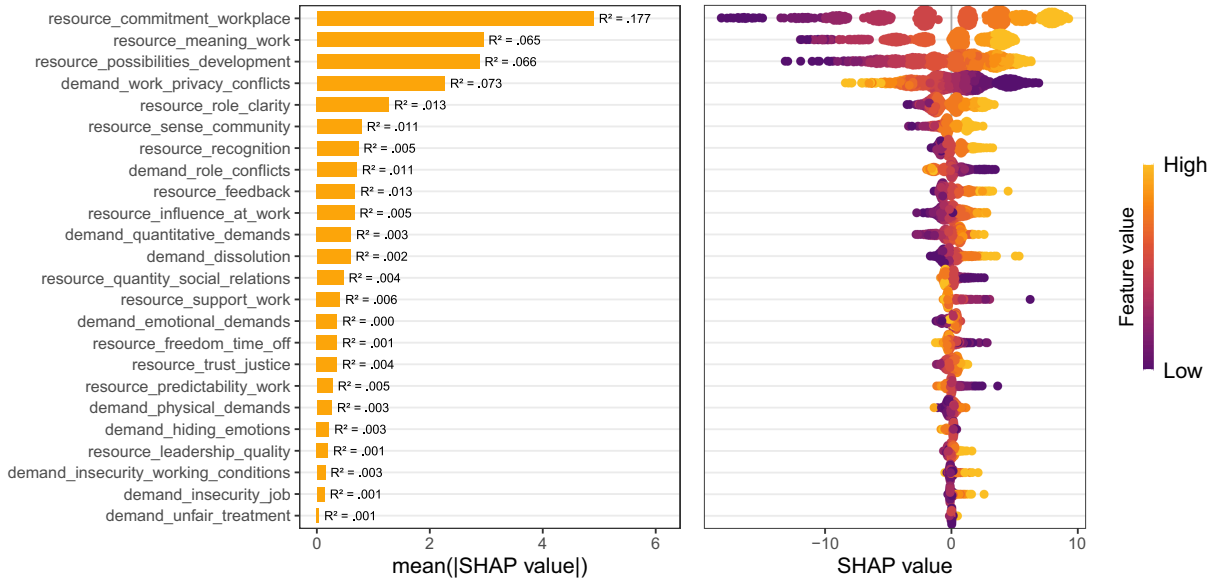
Figure 2
SHAP Values for Predicting Burnout



Note. The left panel shows the mean absolute SHAP values for each job characteristic, reflecting their overall importance in predicting burnout. The right panel displays the distribution of SHAP values across observations, with color indicating the feature value (yellow = high, purple = low) and position showing the direction and strength of importance. The R^2 values indicate the proportion of explained variance attributed to each feature. SHAP = SHapley Additive exPlanations. See the online article for the color version of this figure.

Figure 3

SHAP Values for Predicting Work Engagement



Note. The left panel shows the mean absolute SHAP values for each job characteristic, reflecting their overall importance in predicting work engagement. The right panel displays the distribution of SHAP values across observations, with color indicating the feature value (yellow = high, purple = low) and position showing the direction and strength of importance. The R^2 values indicate the proportion of explained variance attributed to each feature. SHAP = SHapley Additive exPlanations. See the online article for the color version of this figure.

and interaction magnitudes are provided in the Supplemental Material SI-2.

We additionally predicted strain and motivation using a latent factor derived from multiple well-being indicators. These results are reported in the Supplemental Material SI-2 and are highly similar to those for burnout and work engagement presented here, further supporting the robustness of our findings.

Discussion

The present study examined how 24 job characteristics relate to employee well-being (burnout and work engagement) in a large, representative sample of the German workforce using advanced machine learning methods. In contrast to traditional ordinary least squares regression approaches, the machine learning framework used here allowed us to consider higher order interactions among all 24 job characteristics simultaneously and to evaluate their contribution using out-of-sample prediction. As a result, the reported interaction effects reflect patterns that generalize beyond the estimation sample rather than improvements in in-sample fit alone. The models demonstrated that main effects of job characteristics were predictive of burnout and work engagement, while allowing for higher order interactions, reflecting the buffer and boost hypotheses of JD-R, added virtually no explanatory value ($\Delta R^2 \leq 0.8\%$). Work–home conflicts emerged as the strongest predictors of burnout, while workplace commitment, meaning of work, possibilities for development, and work–home conflicts were the strongest predictors of work engagement. These results replicate earlier findings obtained with less representative samples and extend them by showing, with robust predictive methods, that the explanatory power of job characteristics is primarily additive rather than interactive. Together with recent meta-analyses (Gonzalez-Mulé et al., 2021; Huth & Chung-Yan, 2023), our findings suggest that interaction effects do not operate as broadly generalizable mechanisms across jobs and organizations when predicting differences in employee well-being. Importantly, because these meta-analyses were based primarily on studies employing conventional regression approaches, the convergence of findings across analytically distinct methods suggests that the limited contribution of interaction effects is unlikely to be an artifact of the machine learning framework used in the present study. Interpreted in context, the present results reflect between-person patterns, whereas interaction dynamics may unfold differently in within-person or longitudinal processes that capture changes in work characteristics over time. The findings are further situated within a German workforce context and within models estimated across diverse organizations and occupations, emphasizing general patterns across the labor market.

Our findings are consistent with a large body of evidence on the main effects of job demands and resources. Numerous studies show that demands such as workload and emotional demands are most strongly associated with strain, burnout, and exhaustion, whereas resources such as autonomy, feedback, and social support are most reliably associated with higher engagement, commitment, and well-being (Alarcon, 2011; Christian et al., 2011; Crawford et al., 2010; Guthier et al., 2020; Halbesleben, 2010; Knight et al., 2017; Lesener et al., 2020; Mazzetti et al., 2023). The persistence and replicability of these effects across occupations and contexts suggest they are robust and generalizable relationships. Our study corroborates this pattern in a representative sample, showing that demands and

resources each exert meaningful, independent effects on employee well-being. Importantly, our results suggest that the predictive value of demands and resources for employee well-being stems almost entirely from their main effects, with little evidence that any one job characteristic consistently alters the effect of another across jobs.

At the same time, work–home conflicts emerged as a strong predictor in our models, warranting additional discussion. This is consistent with evidence that work–home conflict is a central concern in job design and public health, particularly in Western industrialized countries (e.g., Borgmann et al., 2019; Chandler, 2021; French et al., 2018). Longitudinal research shows that negative work-to-family spillover predicts long-term health outcomes beyond demographics, baseline health, and even traditional job demands (Tsukerman et al., 2020), suggesting that reduced well-being may stem not only from what happens at work but from the extent to which work intrudes on private life and curtails opportunities for recovery (Knecht et al., 2016). Cultural factors may also amplify its prominence in our sample, as Germany's strong norms around work–life separation (Ollier-Malaterre & Foucreault, 2017; Wöhrmann et al., 2016) may foster a stronger preference for segmenting work and personal life (Ashforth et al., 2000; Kossek & Lautsch, 2012; Yang et al., 2000), which in turn is likely to increase sensitivity to work-related intrusions. Another possibility is that work–home conflict functions as a broad meta-stressor that bundles multiple work–life interface challenges—time pressure, cognitive spillover, emotional boundary violations, and technology-enabled availability expectations—into a single, powerful indicator (Grzywacz & Marks, 2000; Michel et al., 2011). We also cannot rule out confounding COVID-19 effects, as noted in the Limitations section.

These results add to a growing body of research (e.g., Gonzalez-Mulé et al., 2021; Huth & Chung-Yan, 2023; Ong & Johnson, 2023) that challenges a central assumption of many prominent stress models: that job characteristics interact in ways that either buffer the negative effects of demands or boost the positive effects of resources. Although we focused on the JD-R model, the demand–control model (Karasek, 1979) and demand–induced strain compensation model (De Jonge & Dormann, 2003) propose similarly unsupported interaction mechanisms (Gonzalez-Mulé et al., 2021; Huth & Chung-Yan, 2023). Ong and Johnson (2023) likewise argued that variable-centered approaches assume universal interactions, overlooking that certain demand combinations (e.g., high workload and emotional demands) may resist buffering even when resources are present. In line with this critique, our predictive modeling shows that including all interactions among job characteristics does not improve accuracy beyond additive models. Together, these findings point to a potential divergence in how interactions may manifest: While they may exist in distinct, configural patterns for certain subgroups, they do not appear to generalize in a way that improves predictive accuracy across employees.

These findings raise the question of why previous studies have reported interactions across employees that do not appear to replicate or generalize. We see three possible explanations. First, interaction effects may be highly job-specific. Our data set reflects cross-job patterns across a wide range of occupations and organizations, meaning that we primarily capture effects that generalize beyond specific job contexts, making our results most relevant to organizational decision making or regulatory policy rather than for individual jobs. It remains possible that within particular occupations or job families, certain interactions do emerge. Even if so, they do not appear to be general mechanisms of occupational health as traditionally assumed in JD-R. Second, apparent interaction effects may arise when only a subset of job characteristics is included. For example, a study might report that high-quality leadership buffers the negative effects of high workload. However, if job control (e.g., autonomy over how and when to perform tasks) is omitted, the interaction term (Leadership × Workload) may be capturing the influence of this unmeasured confounder that affects both leadership (e.g., good leaders tend to grant more autonomy) and well-being (e.g., greater autonomy helps employees manage workload). In this case, the observed moderation would not reflect a true buffer effect but rather a spurious association. Third, many findings rely on in-sample estimation, which increases the risk of overfitting. Models with complex interaction terms often have low power and are more susceptible to capturing random noise. Without cross-validation or replication, such interactions may appear significant in a given data set but lack robustness in other samples or contexts.

Theoretical and Practical Implications

From a theoretical standpoint, our findings underscore the importance of clarifying how interactions are conceptualized and tested in occupational health psychology. To test whether context specificity explains earlier findings, future research should examine whether interactions emerge within particular occupations, industries, or organizational settings (cf. Dierdorff et al., 2025). Our study focused on cross-job, cross-organization patterns, which capture effects that generalize broadly but may overlook mechanisms unique to specific contexts. Running analyses within occupational or industry subsamples would help determine whether JD-R's propositions about buffering and boosting hold locally, even if they do not add predictive value across jobs and organizations. Such approaches also align with cumulative risk perspectives (Lentz et al., 2015; Moretto et al., 2017; Sexton, 2012) and recent large-scale evidence demonstrating the importance of multifactorial models of work stress (Bertrais et al., 2022; Duchaine et al., 2021; Elovainio et al., 2022).

To test whether spurious associations explain earlier findings, future studies should pay greater attention to the causal assumptions underlying interaction models. Focused studies examining a limited set of job characteristics remain valuable for theory development and hypothesis generation. However, when theorizing a specific interaction, researchers should explicitly consider which other job characteristics might act as structural confounders of the focal predictors and employee well-being. Where theoretically justified, researchers should consider whether adjustment for these variables is necessary to reduce the risk that an apparent interaction reflects confounding rather than a genuine buffering or boosting mechanism. Directed acyclic graphs and related causal frameworks may be particularly useful for making such assumptions explicit and identifying appropriate adjustment sets (Pearl, 2009; Rohrer, 2018). Accordingly, confidence in proposed interaction mechanisms should increase when similar findings emerge across studies employing different theoretically grounded model specifications. In this way, focused studies and comprehensive analyses are complementary: The former generate hypotheses about potential mechanisms, whereas the latter can help assess their robustness and generalizability.

To test whether overfitting explains earlier findings, interaction effects should be evaluated by comparing in-sample versus out-of-sample performance. Machine learning approaches, such as those

applied in this study, explicitly separate training and validation samples, helping to quantify the extent to which apparent interactions reflect true signal rather than random noise (Yarkoni & Westfall, 2017). Applying these procedures systematically would provide stronger evidence for or against the robustness of proposed interaction mechanisms.

The present findings also have important implications for practice. Organization-level and government-initiated occupational health and safety interventions within European Union countries place strong emphasis on resource building as a central intervention strategy (Jain et al., 2022), and our results provide clear support for this approach because resources show substantial direct effects on reducing burnout and increasing work engagement. If these strategies rest on the assumption that resources also buffer the effects of high demands by offering protection beyond their main effects, this assumption is not supported. Interactions did not explain additional variance in employee well-being across jobs or companies. Importantly, this does not diminish the relevance of resource-building interventions. Resources such as developmental opportunities, social support, and feedback remain among the strongest predictors of employee well-being (Knight et al., 2017, 2019; Nielsen et al., 2017). What the findings caution against is the managerial assumption that sufficiently increasing resources can compensate for persistently high demands by making those demands less consequential. Instead, resources and demands operate through independent, additive routes, making employee well-being primarily a function of the independent, additive contributions of demands and resources: Resources consistently reduce burnout, while demands consistently increase it. In other words, although higher resources were associated with better employee well-being overall, they did not meaningfully weaken the relationship between demands and employee well-being.

A key distinction is that reducing a demand directly means lowering its level, frequency, or intensity, whereas buffering leaves the demand intact and assumes that additional resources weaken the relationship between the demand and employee strain. Consider work–family conflict: A buffering perspective assumes that supervisor support is especially protective when work–family conflict is high, so that the gap in burnout between supported and unsupported employees widens as conflict increases. Buffering assumes that support blunts the rate at which rising conflict translates to burnout. Instead, support is associated with lower burnout at a fixed rate. In contrast, a demand-reduction perspective focuses on job redesign that reduces work–family conflict itself, for example, by limiting after-hours availability, redesigning work processes to reduce spillover into private life, or establishing norms that protect nonwork time. Our findings provide little evidence for the buffering assumption. Rather than weakening the association between demands and employee well-being, demands and resources were independently associated with employee well-being. Thus, higher demands were associated with poorer well-being, whereas higher resources were associated with better well-being regardless of demand levels, rather than by meaningfully altering the association between demands and well-being. Consequently, because the benefit of resources does not increase as demands rise, adding resources cannot be assumed to offset persistently high demands unless that fixed benefit is large enough to counterbalance the harm those demands impose.

Importantly, some interventions may serve both functions depending on their implementation. For example, flexible work arrangements can act as a resource through greater employee schedule control while also reducing demands if those arrangements structurally limit work from interfering with private life.

This distinction is consistent with occupational health and safety practice and standards such as ISO 45003 (Nebbs et al., 2025), which prioritize eliminating or reducing hazards at their source. Our findings suggest that resource-building interventions remain highly valuable because of their direct positive effects on employee well-being, but organizations should not assume that increasing resources will offset the detrimental effects of persistently high demands through a buffering mechanism. Where demands remain high, reducing those demands through appropriate work redesign is likely to be a more effective strategy than relying on additional resources to compensate for them. This pattern aligns with the resource caravan principle in conservation of resources theory (Hobfoll, 2011) and with the main direct effects outlined in the second proposition of the JD-R model.

Limitations and Directions for Future Research

Our study has several limitations that warrant consideration. First, our study is limited to between-person differences nested within organizations, which restricts generalization to within-person fluctuations and alternative clustering such as job roles. Short-term, dynamic studies suggest that interaction effects may emerge at the intraindividual level (e.g., Gerpott et al., 2022; Sonnentag et al., 2025; Xanthopoulou et al., 2012). Although we clustered employees within organizations, reflecting the role of leadership and culture, job roles may also matter, as the relevance of work attributes varies across occupations (Dierdorff et al., 2025). Future research should therefore integrate longitudinal designs with multilevel approaches that capture both intraindividual dynamics and occupation-specific contexts.

Second, our study identifies associations but cannot address causal direction, counterfactual outcomes, or more complex dynamic relationships (Pearl, 2009). Because of our cross-sectional design, we cannot test moderated mediations, bidirectional effects, or temporal dynamics. For instance, job control may foster work engagement, but engaged employees may also secure more control, and burnout symptoms can increase perceived demands (Guthier et al., 2020). Future research should integrate causal inference frameworks with machine learning (e.g., double machine learning; Chernozhukov et al., 2018; Freiesleben & Molnar, 2024) to better adjust for confounding and disentangle causal relationships.

Third, our study does not include additional conceptual factors that may shape how employees experience work: personal traits (e.g., optimism, self-efficacy, neuroticism), subjective appraisals of demands (challenge vs. hindrance; Bakker & Sanz-Vergel, 2013; Cavanaugh et al., 2000), and demand–resource matching (De Jonge & Dormann, 2006). These mechanisms are not captured in the COPSOQ, though we expect their predictive contribution to be primarily additive, given that even theoretically aligned combinations (e.g., Emotional Demands × Social Support) showed no incremental predictive value. Future research should include such elements to test whether interactions matter under more targeted conditions.

Fourth, the present findings should be interpreted within their broader contextual and methodological setting. Part of the data was collected during the COVID-19 pandemic, a period characterized by substantial changes in work arrangements and daily routines that

may have influenced the salience of specific job characteristics and outcomes, potentially shaping their relative importance in the analyses. Moreover, the sample consisted exclusively of German employees, and cultural or institutional differences across labor markets may lead to different patterns of associations in other contexts (Henrich et al., 2010). All measures were based on self-reports, which may introduce biases related to memory, response styles, or social desirability (e.g., Bradburn et al., 1987; Heine et al., 2002; Holden & Passey, 2009; Van Vaerenbergh & Thomas, 2013). Together, these factors suggest that the results reflect patterns observed within a specific temporal, cultural, and measurement context. Replication across postpandemic samples, diverse cultural settings, and studies incorporating non-self-reported indicators such as absenteeism, turnover, or physiological markers (e.g., Schlotz et al., 2004) will be important for assessing the robustness and generalizability of the reported findings.

Conclusion

In conclusion, across multiple analytic approaches and outcomes, interaction effects provided little incremental predictive value beyond the additive contributions of individual job characteristics. Improvements in out-of-sample performance from models allowing nonlinearities and interactions were minimal, suggesting that differences in employee well-being were primarily associated with the independent effects of demands and resources rather than their combinations. Interpreted within the context of a German quota sample based on self-reported work characteristics and well-being indicators, these findings highlight the central role of core job characteristics in explaining employee outcomes and suggest that additive models capture most of the predictive signal across diverse jobs and organizations.

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