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Linking technology readiness and the job demands–resources framework: how generative AI shapes work in small and medium enterprises?

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Abstract

Purpose – This study aims to examine how individual technology readiness shapes employees' perceptions of generative artificial intelligence (GenAI) as a job resource and/or a job demand, and how these appraisals influence engagement, exhaustion and performance in small and medium enterprises (SMEs).

Design/methodology/approach – Survey data were collected from 465 UK SME employees who regularly use GenAI. The study integrates the technology readiness index (TRI) with the job demands–resources (JD–R) framework and tests the model using covariance-based structural equation modeling and multigroup analysis.

Findings – Optimism increases artificial intelligence (AI)-related job resources, while innovativeness, insecurity and discomfort primarily increase job demands. Resources enhance engagement, whereas demands increase exhaustion, which in turn reduces engagement. Engagement is the main predictor of employee performance. Effects are stronger in smaller firms.

Research limitations/implications – The cross-sectional design and self-reported data limit causal inference and generalizability. The study advances theory by showing that GenAI operates simultaneously as a job resource and a demand, with asymmetric effects shaped by technology readiness.

Practical implications – SMEs should actively reduce AI-related demands (e.g. cognitive load, validation effort) while strengthening resources such as training and workflow integration, prioritizing engagement to improve performance.

Social implications – The impact of GenAI depends on employee experience: it can enhance well-being when perceived as a resource but increase strain when experienced as a demand.

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Originality/value – The study integrates TRI and JD–R to explain how individual technological predispositions shape AI-related work experiences and performance in SMEs.

Keywords Generative AI, Technology readiness, Job demands–resources, Work engagement, Employee performance, SMEs

Paper type Research paper

1. Introduction

Despite rapid advances in generative artificial intelligence (GenAI), empirical evidence remains limited on how individual differences in technology attitudes shape employees' appraisal of artificial intelligence (AI)-specific job demands and resources, and how these appraisals influence strain, motivation and performance (Scholze and Hecker, 2024; Zhou *et al.*, 2024). While GenAI can enhance routine workflows and decision-making, its use also entails cognitive, learning and validation costs that may increase job demands. Employees' perceptions of AI are further shaped by contextual and normative organizational evaluations (Zhang and Soderberg, 2026), reinforcing the importance of examining how GenAI is cognitively appraised as either a resource or a demand. However, existing research has not yet fully clarified how these contrasting effects emerge at the individual level in everyday work contexts.

Marimon *et al.* (2025) show that innovation-oriented employees are more likely to adopt GenAI early and that readiness for new technologies correlates with greater engagement. The technology readiness index (TRI) (Parasuraman and Colby, 2015) offers a multidimensional account of such predispositions – optimism, innovativeness, discomfort and insecurity – but has rarely been systematically embedded within occupational stress frameworks. In parallel, job demands–resources (JD–R) theory (Bakker *et al.*, 2023) proposes dual pathways linking resources to engagement and demands to exhaustion and performance, while calling for greater attention to person × situation dynamics. Yet, existing JD–R research seldom distinguishes technology-specific demands and resources from general job characteristics nor does it typically model stable technology attitudes as antecedents shaping those appraisals (Scholze and Hecker, 2024). In addition, research indicates that employees' perceptions of AI are influenced by organizational contexts, including human resource management practices (Fenwick *et al.*, 2024) and the integration of exploratory and exploitative learning processes enabled by AI (Liu, 2024), highlighting that both individual and organizational factors shape how GenAI is experienced.

These gaps are particularly salient in small and medium enterprises (SMEs), which play a central role in modern economies, accounting for most firms and contributing significantly to employment and economic growth [Organisation for Economic Co-operation and Development (OECD), 2023]. In this context, their structural characteristics amplify the relevance of employee-level mechanisms. SMEs face significant resource constraints when implementing digital transformation, including limited financial slack, reduced access to specialized expertise and less formalized organizational processes (Sultan and Riyadh, 2025; Thong, 1999). Unlike large organizations, SMEs typically lack dedicated IT departments and structured change management practices, making technology adoption more dependent on individual employees' skills and attitudes (Maroufkhani *et al.*, 2020; Scuotto *et al.*, 2017). As a result, employee-level mechanisms become particularly important in explaining how new technologies are adopted and experienced in these contexts.

In addition, SMEs are characterized by higher informality and lower role specialization, which increases employees' exposure to multiple demands and responsibilities (Kotey and Slade, 2005). This intensifies the impact of new technologies such as GenAI, as employees must learn and integrate these tools into their daily work without extensive organizational support. As a result, individual technological predispositions become a critical determinant of whether GenAI is experienced as a job resource that enhances task efficiency or as a job demand that increases cognitive load and oversight burden (Marimon *et al.*, 2025). This underscores the need to understand how individual differences shape AI-related work experiences in SME settings. This heightened dependence on individual-level factors directly affects people–performance relationships within SMEs (Sparrow and Cooper, 2014). In such contexts, where organizational support structures are limited, employees' interpretations and experiences of new technologies become central in shaping work outcomes. Accordingly, a theoretical lens that captures both the positive and negative implications of these experiences is required.

The JD–R framework is particularly suitable in this regard, as it enables the examination of how employees' appraisals of GenAI – as either a job resource or a job demand – translate into distinct psychological processes. Specifically, GenAI may function as a resource that fosters motivation and engagement or as a demand that increases strain and exhaustion, with both pathways ultimately influencing performance outcomes (Costa *et al.*, 2015; Du *et al.*, 2022; Zeijen *et al.*, 2020).

Building on this perspective, integrating TRI with the JD–R framework allows for a more comprehensive understanding of individual differences in responses to GenAI. By explicitly incorporating AI-specific job demands and resources, this approach addresses an important theoretical and empirical gap. In particular, it enables the examination of how employees' technological predispositions shape their experiences with GenAI in SMEs and, through both motivational (engagement) and health-impairment (exhaustion) pathways, influence performance outcomes (Scholze and Hecker, 2024).

Accordingly, this study seeks to address the following research questions:

RQ1. how does GenAI use in SMEs affect employee performance through engagement and exhaustion, and

RQ2. how are these effects shaped by employees' technological predispositions?

To answer these questions, the study pursues two interconnected objectives. First, from a psychological perspective, it examines how technological readiness shapes employees' appraisal of GenAI as either a job resource or a job demand, thereby influencing engagement and exhaustion. Second, from a management and efficiency perspective, it analyses how these micro-level appraisals translate into observable employee performance outcomes.

The remainder of the article is structured as follows. Section 2 develops the theoretical framework and hypotheses. Section 3 outlines the methodology. Section 4 presents empirical findings. Section 5 discusses contributions, limitations and future research directions.

2. Theoretical framework

The diffusion of GenAI reshapes job characteristics and employee experiences, requiring theoretical integration between technology adoption perspectives and occupational well-being frameworks. As GenAI becomes embedded in daily work processes, employees' technological predispositions shape how they appraise AI-related changes, which in turn influence motivation, strain and performance. To capture this dynamic, the present study integrates the TRI (Parasuraman and Colby, 2015), the JD–R model (Demerouti *et al.*, 2001; Bakker *et al.*, 2023) and the dual engagement–exhaustion pathway (Schaufeli *et al.*, 2002). This integration provides a structured framework for explaining how individual technological predispositions shape AI-related work experiences and how these experiences translate into employee outcomes.

Building on prior research, the extant literature provides a coherent basis for theorizing a sequence of relationships between AI and employee-related outcomes in the workplace. First, there is broad agreement that AI is no longer external to organizational contexts but is increasingly embedded within them. In this regard, Seeber *et al.* (2020) argue that "AI machines became teammates rather than tools," highlighting a fundamental shift in how technology is conceptualized in work systems. This transformation suggests a reconfiguration of human–technology interaction, where AI actively participates in task execution and decision-making processes.

Building on this premise, Zirar *et al.* (2023) note that although there is extensive evidence on the value AI can generate for organizations, "research on how workers and AI can coexist in workplaces is evolving." This observation points to an emerging but still fragmented research stream, particularly regarding the implications of AI for employees' psychological and behavioral outcomes.

A substantial body of literature has focused on the potential risks associated with AI in the workplace, often framed as a "double-edged sword" or emphasizing its "dark side" (Liang *et al.*, 2022; Scholze and Hecker, 2024; Zhou *et al.*, 2024). These studies consistently highlight adverse consequences for employees, including increased job insecurity (Yam *et al.*, 2023), emotional exhaustion driven by heightened work demands (Teng *et al.*, 2024), burnout (Kong *et al.*, 2021) and deterioration in mental health (Kim *et al.*, 2024). Collectively, this stream underscores the strain-inducing mechanisms through which AI may negatively affect employee well-being.

However, a smaller but growing body of research adopts a more positive perspective, examining the potential benefits of AI for employees. For instance, AI-related work contexts have been associated with higher levels of engagement (Ogunfowora *et al.*, 2022; Bankins and Formosa, 2023), increased passion for work (Pollack *et al.*, 2020) and enhanced perceptions of meaningful work (Blustein *et al.*, 2023). These positive psychological states are, in turn, linked to favorable organizational outcomes, such as improved efficiency (Kim *et al.*, 2024) and greater psychological empowerment (Llorente-Alonso *et al.*, 2024).

Taken together, the literature suggests a dual-path framework in which AI in the workplace can simultaneously generate both detrimental and beneficial employee outcomes. This duality provides a strong theoretical foundation for examining the mechanisms through which AI influences employee experiences and, ultimately, organizational performance.

The framework posits that technology readiness shapes perceptions of AI-specific job resources and demands, which subsequently activate motivational and health-impairment processes that determine performance.

2.1 Technology readiness and AI appraisal

Technology readiness reflects an individual's propensity to embrace new technologies to achieve goals. TRI distinguishes two enabling dimensions – optimism and innovativeness – and two inhibiting dimensions – discomfort and insecurity (Parasuraman and Colby, 2015). Optimism captures beliefs that technology enhances efficiency and control, whereas innovativeness reflects the tendency to experiment with and pioneer new technologies. Discomfort and insecurity represent feelings of being overwhelmed or doubtful about technology's reliability and one's competence.

In the context of GenAI, these dispositions are critical. Optimistic employees are likely to interpret AI as a supportive tool that enhances autonomy, creativity and efficiency (Pollack *et al.*, 2020; Kim *et al.*, 2024). Innovativeness may encourage deeper experimentation, potentially exposing individuals to both opportunities and complexity. Conversely, insecurity and discomfort may heighten perceptions of technological threat, cognitive burden and job vulnerability (Yam *et al.*, 2023; Zhou *et al.*, 2024). TRI thus provides the dispositional foundation explaining why employees differ in their appraisal of GenAI as a job resource or a job demand.

2.2 AI-specific job resources and demands (JD–R framework)

JD–R theory posits that job characteristics can be classified as demands or resources, which trigger distinct psychological processes (Demerouti *et al.*, 2001; Bakker *et al.*, 2023). Job resources facilitate goal attainment and personal growth, while job demands require sustained effort and may deplete energy.

GenAI introduces both simultaneously. AI-specific resources include cognitive support, efficiency gains, feedback enhancement and skill development opportunities. These affordances can free cognitive capacity and foster engagement. At the same time, AI introduces new demands such as cognitive complexity, accountability ambiguity, continuous skill updating and oversight workload. Empirical evidence suggests that AI awareness may increase emotional exhaustion and withdrawal behaviors (Nguyen and Nguyen, 2025), reinforcing the classification of AI-related pressures as job demands.

Distinguishing AI-specific resources and demands operationalizes JD–R within digital transformation contexts, highlighting that technology reshapes not only tasks but also how work is experienced.

2.3 Engagement and exhaustion as dual pathways to performance

JD–R's central contribution lies in its dual-pathway logic. Job resources activate a motivational process that fosters work engagement, whereas job demands trigger a health-impairment process leading to exhaustion (Schaufeli *et al.*, 2002; Bakker *et al.*, 2023).

Work engagement – characterized by vigor, dedication and absorption – emerges when employees possess sufficient resources. In AI-augmented settings, cognitive support and efficiency gains may strengthen intrinsic motivation and task involvement. In contrast, sustained exposure to AI-specific demands drains personal resources and induces exhaustion.

These pathways converge at employee performance. Engagement promotes persistence, adaptability and creativity in interacting with GenAI systems (Schaufeli *et al.*, 2002; Du *et al.*, 2022). Exhaustion depletes attention and self-regulation, undermining effectiveness. Evidence suggests that performance is more strongly driven by motivational activation than by the mere absence of strain (Anlesinya and Susomrith, 2025).

Accordingly, GenAI's performance implications depend on the balance between resources and demands it generates. When experienced as resource-enhancing, GenAI should improve engagement and performance; when perceived as demand-intensifying, it should increase exhaustion and indirectly reduce effectiveness.

2.4 Integrative conceptual model and hypotheses

The proposed model conceptualizes a causal chain in which TRI dimensions influence AI-specific job resources and demands, which activate engagement and exhaustion, ultimately shaping performance (Figure 1).

The remainder of this section develops and justifies our hypotheses on the extant literature. First, as stated above, technology readiness reflects individuals' propensity to embrace or resist new technologies, shaping whether they are perceived as opportunities or threats (Parasuraman and Colby, 2015). Positive dimensions (optimism and innovativeness)

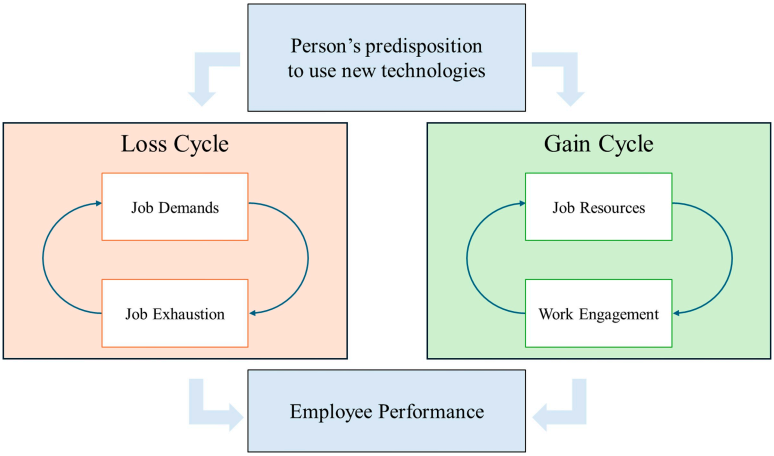

Figure 1. Theoretical model adapted for job resource–demand framework
Source: Bakker *et al.* (2023)

are associated with favorable evaluations of technology, whereas negative dimensions (insecurity and discomfort) tend to generate more adverse perceptions. In line with prior research suggesting that digital technologies can be experienced as a "double-edged sword" (Liang *et al.*, 2022), these predispositions are expected to influence whether GenAI is appraised as a job resource or a job demand. Specifically, enabling dimensions (optimism and innovativeness) are expected to be more positively associated with AI-related resources, whereas inhibiting dimensions (insecurity and discomfort) are expected to be more strongly related to AI-related demands:

H1. Optimism impacts GenAI job resources.

H2. Optimism impacts GenAI job demands.

H3. Innovativeness impacts GenAI job resources.

H4. Innovativeness impacts GenAI job demands.

H5. Insecurity impacts GenAI job resources.

H6. Insecurity impacts GenAI job demands.

H7. Discomfort impacts GenAI job resources.

H8. Discomfort impacts GenAI job demands.

According to the JD–R framework, job resources foster motivation and engagement, 6whereas job demands generate strain and exhaustion (Bakker and Demerouti, 2017):

H9. GenAI job resources impact work engagement.

H10. GenAI job demands impact exhaustion.

The JD–R model further suggests that exhaustion can influence motivational states such as engagement (Bakker and Demerouti, 2017):

H11. Exhaustion impacts work engagement.

Engagement represents a motivational pathway linked to performance, whereas exhaustion reflects a health-impairment process associated with reduced effectiveness (Costa *et al.*, 2015; Zeijen *et al.*, 2020):

H12. Work engagement impacts employee performance.

H13. Exhaustion impacts employee performance.

These hypotheses form the research model presented in Figure 2.

3. Methodology

3.1 Questionnaire design

A structured questionnaire was developed to measure technology readiness, AI-specific job resources and demands, work engagement, exhaustion and employee performance. Items were adapted from established scales to ensure validity and reliability (see Table 1). Technology readiness was measured using the four TRI dimensions proposed by Parasuraman and Colby (2015). The remaining constructs were operationalized using validated items commonly used in JD–R research.

All items were measured using Likert-type scales. A pilot test with a small group of professionals and academic colleagues ensured clarity and content validity before full deployment.

3.2 Sample and data collection

Data were collected in November 2024 through an online survey administered via Qualtrics. Participants were recruited through Prolific, a widely used academic research platform known for high data quality and attention reliability (Douglas *et al.*, 2023). Prior studies have

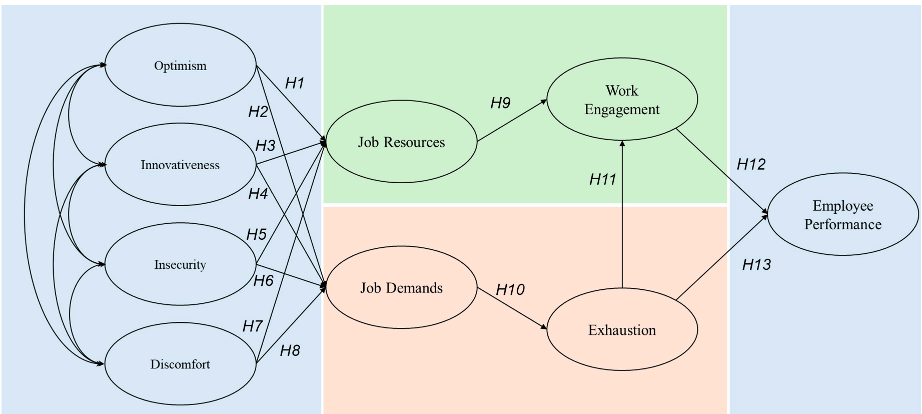

Figure 2. Research model

Table 1. Items proposed for the questionnaire

S. No.	Construct	Code	Item
1	Optimism	OP1	New technologies contribute to a better quality of life
2		OP2	Technologies give people more control over their daily life
3		OP3	I feel optimistic about the use of new technologies
4	Innovativeness	IN1	Other people come to me for advice on new technologies
5		IN2	In general, I am among the first in my circle of friends to acquire new technology when it appears
6		IN3	I can usually figure out new high-tech products and services without help from others
7	Insecurity	IS1	People are too dependent on technology to do things for them
8		IS2	Too much technology distracts people to a point that is harmful
9		IS3	I do not feel confident doing business with a service that can only be reached online
10	Discomfort	DI1	When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do
11		DI2	Technical support lines are not helpful because they do not explain things in terms that I understand
12		DI3	Sometimes, I think that technology systems are not designed for use by ordinary people
13	Job resources	JR1	My workplace provides adequate resources to use GenAI tools
14		JR2	I receive training to use GenAI effectively
15		JR3	I have access to tools that simplify my work using GenAI
16	Job demands	JD1	The use of generative AI tools in my job requires significant mental effort to interpret and validate the outputs
17		JD2	I need to continually update my skills to effectively use and manage generative AI tools in my job
18		JD3	The use of generative AI tools in my job creates pressure to deliver faster results
19		JD4	The complexity of overseeing tasks generated by generative AI tools adds additional workload to my job
20	Work engagement	WE1	At work, I feel bursting with energy
21		WE2	At my job, I feel strong and vigorous
22		WE3	I am enthusiastic about my job
23	Exhaustion	EX1	My work leaves me mentally exhausted
24		EX2	My work makes me feel worn out
25		EX3	My work makes me feel tired
26	Employee performance	EP1	I maintain a high standard of work
27		EP2	I consistently complete my tasks on time
28		EP3	I know I can handle multiple assignments for achieving organizational goals

shown that Prolific provides reliable and high-quality data, often outperforming other online panels in terms of participant attention and response validity. Eligibility criteria required respondents to:

- work full-time in UK-based SMEs (fewer than 250 employees);
- use generative AI tools at least once per week;
- have at least five months in their current role;

- have at least one year of work experience; and
- maintain a 100% Prolific approval rate.

The final sample consisted of 465 complete responses. The demographic distribution is summarized in Table 2. The sample included employees from micro-sized (1–9 employees), small-sized (10–49) and medium-sized (50–249) firms, with varied tenure and frequent GenAI usage (Table 2).

3.3 Measurement validation and model assessment

The analysis followed a two-stage approach.

First, exploratory factor analyses (EFA) using principal component analysis with varimax rotation were conducted to assess dimensionality. The TRI items confirmed the four-factor structure of optimism, innovativeness, insecurity and discomfort (Parasuraman and Colby, 2015). Separate EFAs for job resources, job demands, engagement, exhaustion and performance yielded single-factor solutions. Items with loadings below 0.70 were removed. Retained items met established thresholds for factor loadings and item-to-total correlations (Ladhari, 2012; Wolfinbarger and Gilly, 2003).

Second, the structural model was tested using covariance-based structural equation modeling (SEM-CB) with robust maximum likelihood estimation in structural equations program (software package for structural equation modelling) (EQS). SEM-CB is particularly suitable for testing theoretically grounded models with latent constructs and hypothesized relationships, as it allows for the simultaneous estimation of measurement and structural models and provides a rigorous assessment of overall model fit. Given the confirmatory nature of our study and its strong theoretical foundation in the JD-R framework, SEM-CB is an appropriate analytical technique. Reliability was assessed using Cronbach's alpha and composite reliability (CR), and convergent validity using average variance extracted (AVE), following recommended criteria (Hair *et al.*, 2010; Nunnally and Bernstein, 1994). Discriminant validity was evaluated using the Fornell and Larcker (1981) criterion and the heterotrait–monotrait ratio (HTMT).

Model fit was examined using the Satorra–Bentler chi-square statistic, comparative fit index (CFI), and root mean square error of approximation (RMSEA). These indices provided evidence of adequate model fit.

3.4 Multigroup analysis

To examine whether structural relationships differed by organizational size, a multigroup analysis (MGA) was conducted using EQS. The sample was divided into two groups: firms with fewer than 50 employees ($n = 243$) and firms with 50–249 employees ($n = 222$). This procedure tested the invariance of structural paths across small- and medium-sized firms.

4. Results

This section presents the measurement validation, structural model findings and multigroup comparisons. First, we assessed the potential presence of common method variance using Harman's one-factor test by conducting an unrotated principal components analysis of all questionnaire items (Harman, 1976). The analysis yielded eight components with eigenvalues greater than 1, with the first component accounting for 28.7% of the total variance. Since this proportion is well below the 50% threshold, the results suggest that common method bias is not a serious concern in this study (Podsakoff *et al.*, 2003).

Table 2. Demographic characteristics of the sample

Characteristic	No.	%
Gender		
Male	262	56.3
Female	200	43.0
Non-binary	1	0.2
Prefer not to say	2	0.4
Total	465	100.0
Age (years)		
18–24	35	18–24
25–34	186	25–34
35–44	134	35–44
45–54	81	45–54
55–64	29	55–64
Total	465	Total
Experience (years in the current position)		
5–6 months	10	2.2
7–12 months	25	5.4
1–2 years	88	18.9
2–5 years	139	29.9
More than 5 years	203	43.7
Total	465	100.0
Frequency of GenAI use		
Once a week	98	21.1
Two to six times a week	224	48.2
Every day	89	19.1
Multiple times every day	54	11.6
Total	465	100.0
Company size (number of employees)		
1–9	97	1–9
10–49	145	10–49
50–249	223	50–249
Total	465	Total

4.1 Measurement validation and structural model fit

EFA confirmed the expected dimensional structure (Table 3). The TRI construct retained four distinct dimensions – optimism, innovativeness, insecurity and discomfort – consistent with Parasuraman and Colby (2015). The remaining constructs (job resources, job demands, engagement, exhaustion and performance) each demonstrated single-factor solutions. Items loading below 0.70 were removed (Table 4).

Reliability and validity indicators met recommended thresholds (Table 5). Cronbach's alpha and CR values exceeded 0.70 for all constructs except discomfort ($\alpha = 0.595$), though its CR and AVE were acceptable (Hair *et al.*, 2010; Nunnally and Bernstein, 1994). Convergent validity was confirmed through AVE values above 0.50, and discriminant validity was supported using both the Fornell–Larcker criterion (Fornell and Larcker, 1981) (Table 6) and HTMT ratios (all below 0.60).

The SEM-CB model demonstrated satisfactory fit: Satorra–Bentler χ^2 (df = 256) = 465.08; χ^2/df = 1.82; RMSEA = 0.042; CFI = 0.945. These indices indicate adequate representation of the data (Hair *et al.*, 2010).

Table 3. Matrixes of the components extracted using principal components analyses and varimax rotation

Item	1 Optimism	2 Innovativeness	3 Insecurity	4 Discomfort
OP1	0.854	*0.137*	*−0.086*	*−0.114*
OP2	0.791	*0.031*	*−0.166*	*−0.116*
OP3	0.778	*0.171*	*−0.206*	*−0.061*
IN2	*0.181*	0.832	*−0.164*	*0.045*
IN1	*0.091*	0.819	*−0.084*	*−0.034*
IN3	*0.021*	0.757	*0.052*	*−0.228*
IS1	*−0.181*	*−0.086*	0.814	*0.034*
IS2	*−0.272*	*−0.061*	0.799	*0.022*
IS3	*0.005*	*−0.083*	*0.516*	*0.404*
DI2	*−0.110*	*−0.063*	*0.076*	0.799
DI3	*−0.075*	*−0.052*	*0.030*	0.773
DI1	*−0.209*	*−0.386*	*0.159*	*0.417*

Note(s): In italic loads under 0.7; One EFA using the items pertaining to the four subdimensions of the construct "Technology readiness"

Table 4. Five independent EFAs for the rest of the constructs of the model

5 Job resources		6 Job demands		7 Work engagement		8 Exhaustion		9 Employee performance	
JR1	0.845	JD3	0.865	EN2	0.905	EX2	0.945	EP2	0.828
JR2	0.795	JD1	0.800	EN1	0.899	EX1	0.921	EP3	0.819
JR3	0.758	JD4	0.798	EN3	0.849	EX3	0.913	EP1	0.774
		JD2	*0.667*						

Note(s): In italic loads under 0.7

4.2 Technology readiness as antecedent of AI-specific resources and demands

The structural results reveal a clear asymmetry in how TRI dimensions shape AI-related job appraisals (Table 7; Figure 3).

Optimism positively predicts AI-specific job resources ($\beta = 0.251$, $t = 2.81$; *H1* supported) but does not significantly reduce job demands (*H2* not supported). Thus, optimism operates as a resource-enhancing disposition rather than a demand-buffering mechanism.

Innovativeness does not significantly predict job resources (*H3* not supported) but increases AI-specific job demands ($\beta = 0.272$, $t = 3.99$; *H4* supported). This suggests that more innovative employees may engage more intensively with GenAI, thereby encountering greater complexity or validation pressures.

The negatively valenced dimensions show a consistent pattern. Insecurity strongly predicts higher job demands ($\beta = 0.333$, $t = 3.18$; *H6* supported) but does not influence resources (*H5* not supported). Discomfort also increases job demands ($\beta = 0.215$, $t = 3.70$; *H8* supported) without significantly affecting resources (*H7* not supported).

Overall, only optimism increases AI-specific resources, whereas innovativeness, insecurity and discomfort primarily elevate AI-specific demands. Insecurity emerges as the strongest predictor of perceived demands.

Table 5. Loads of the constructs and statistics for their reliability analyses

Optimism	1 Optimism		2 Innovativeness		3 Insecurity		4 Discomfort		5 Job resources		6 Job demands		7 Work engagement		8 Exhaustion		9 Employee performance	
	OP1	0.854	IN2	0.832	IS1	0.814	DI2	0.799	JR1	0.845	JD3	0.865	WE2	0.905	EX2	0.945	EP2	0.828
	OP2	0.791	IN1	0.819	IS2	0.799	DI3	0.773	JR2	0.795	JD1	0.800	WE1	0.899	EX1	0.921	EP3	0.819
	OP3	0.778	IN3	0.757					JR3	0.758	JD4	0.798	WE3	0.849	EX3	0.913	EP1	0.774
Cronbach's alpha	0.783		0.760		0.771		0.595		0.710		0.788		0.860		0.917		0.771	
Composite reliability	0.850		0.845		0.788		0.764		0.842		0.862		0.915		0.948		0.849	
Average variance extracted	0.653		0.645		0.650		0.618		0.800		0.675		0.783		0.858		0.652	

Table 6. Correlation matrix of latent factors

Latent factors	1	2	3	4	5	6	7	8	9
1 Optimism	*0.749*								
2 Innovativeness	0.377	*0.730*							
3 Insecurity	−0.545	−0.290	*0.747*						
4 Discomfort	−0.339	−0.236	0.276	*0.663*					
5 Job resources	0.266	0.156	−0.095	−0.210	*0.688*				
6 Job demands	−0.044	0.165	0.255	0.207	−0.006	*0.657*			
7 Work engagement	0.058	0.018	−0.040	−0.060	0.205	−0.083	*0.824*		
8 Exhaustion	−0.009	0.035	0.053	0.043	−0.001	0.210	−0.390	*0.888*	
9 Employee performance	0.030	0.013	−0.016	−0.028	0.111	−0.024	0.502	−0.110	*0.695*

Note(s): In the main diagonal the square of AVEs; Values in italics on the main diagonal represent the square root of the AVE for each construct

Table 7. Standardized coefficients with *t*-values associated for the 13 hypothesis

Hypothesis	Standardized coefficient	*t*-value	Result
H1. Optimism impacts on job resources specific	0.251	2.81	Accepted
H2: Optimism impacts on job demands specific	0.108	1.28	Refused
H3. Innovativeness impacts on job resources specific	0.057	0.78	Refused
H4. Innovativeness impacts on job demands specific	0.272	3.99	Accepted
H5. Insecurity impacts on job resources specific	0.097	1.17	Refused
H6. Insecurity impacts on job demands specific	0.333	3.18	Accepted
H7. Discomfort impacts on job resources specific	−0.139	−1.73	Refused
H8. Discomfort impacts on job demands specific	0.215	3.70	Accepted
H9. Job resources specific impacts on work engagement	0.205	3.21	Accepted
H10. Job demands specific impacts on exhaustion	0.210	3.70	Accepted
H11. Exhaustion impacts work engagement	−0.389	−7.35	Accepted
H12. Work engagement impacts on employee performance	0.543	7.25	Accepted
H13. Exhaustion impacts on employee performance	0.102	1.81	Refused

4.3 Engagement, exhaustion and performance dynamics

Consistent with JD–R theory, AI-specific job resources positively affect work engagement ($\beta = 0.205$, $t = 3.21$; *H9* supported), whereas AI-specific job demands increase exhaustion ($\beta = 0.210$, $t = 3.70$; *H10* supported).

Exhaustion significantly reduces engagement ($\beta = -0.389$, $t = -7.35$; *H11* supported). Engagement strongly predicts employee performance ($\beta = 0.543$, $t = 7.25$; *H12* supported), whereas the direct effect of exhaustion on performance is nonsignificant (*H13* not supported).

These findings indicate that performance is primarily driven by the motivational pathway. AI-related demands affect performance indirectly through exhaustion's negative effect on engagement rather than through a direct strain-performance link. Engagement thus emerges as the central driver of effectiveness in AI-enabled SME contexts.

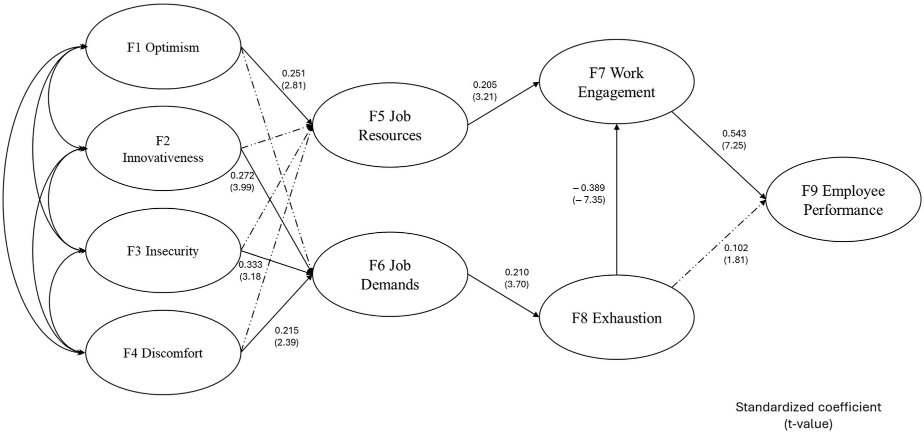

Figure 3. Research model with standardized coefficients and *t*-values associated (dotted lines for nonsignificant paths)

4.4 Multigroup analysis by organizational size

A MGA compared firms with fewer than 50 employees ($n = 243$) and those with 50–249 employees ($n = 222$). Most structural relationships remained stable across groups.

However, as shown in Table 8, the effect of job demands on exhaustion was stronger in smaller firms (β = 0.237 vs 0.200). Likewise, the engagement–performance relationship was slightly stronger in smaller organizations (β = 0.551 vs 0.536). The path from exhaustion to performance remained weak and nonsignificant in both groups.

These results suggest that in smaller firms, AI-related demands more strongly translate into exhaustion, and engagement plays an even more central role in determining performance.

Two additional multigroup analyses were conducted to assess the potential moderating effects of gender and age, comparing male vs female respondents and employees younger than 35 years vs those older than 35 years. The results indicate no significant differences in structural paths across groups, supporting the invariance of the model.

These findings indicate that organizational size matters, as structural relationships vary between smaller and medium-sized firms, whereas no differences emerge for gender or age. In smaller firms, the stronger effects of job demands on exhaustion and of engagement on performance suggest a greater reliance on individual-level processes. This is consistent with prior research showing that SMEs depend more on employees' capabilities and face lower levels of formalization and support (Kotey and Slade, 2005; Thong, 1999). Accordingly, firm size helps explain differences in how GenAI-related demands and resources translate into employee outcomes.

4.5 Results summary

The findings demonstrate a systematic asymmetry in technology readiness effects. Optimism enhances AI-specific job resources, whereas innovativeness, insecurity and discomfort primarily increase AI-specific demands. Within the JD–R framework, resources stimulate engagement, demands generate exhaustion and engagement serves as the dominant predictor of employee performance. The direct impact of exhaustion on performance is negligible once engagement is accounted for.

Table 8. Structural paths that differ between groups (final multigroup results)

Path (latent)	Group A (≤10 emp; n = 243)	Group B (>10 emp; n = 222)
Job demands → exhaustion	Unstd = 0.402; t = 3.92; Std ≈ 0.237	Unstd = 0.402; t = 3.92; Std ≈ 0.200
Work engagement → employee performance	Unstd = 0.255; t = 7.22; Std ≈ 0.551	Unstd = 0.255; t = 7.22; Std ≈ 0.536
Exhaustion → employee performance	Unstd = 0.039; t = 1.783; Std ≈ 0.10; p ≈ 0.10	Unstd = 0.039; t = 1.783; Std ≈ 0.095; p ≈ 0.09

Moreover, these dynamics are slightly amplified in smaller SMEs, where demands more strongly increase exhaustion and engagement more strongly predicts performance. Overall, GenAI's organizational consequences depend on whether it is experienced as a resource that energizes employees or as a demand that depletes them. This finding aligns with recent research demonstrating that AI-related perceptions elevate emotional exhaustion and downstream negative work behaviors (Nguyen and Nguyen, 2025). Practically, these results imply that SME managers should prioritize interventions that reduce AI-related demands and protect employees from exhaustion (e.g. by streamlining validation tasks, allocating time for learning and establishing simple governance), while also building resources and capitalizing on optimism where possible. Consistent with recent research on innovation and sustainability in SMEs, effective technology adoption requires balancing resource limitations with strategic adaptation (Franco *et al.*, 2025).

5. Discussion, limitations and future research

5.1 Discussion and theoretical implications

This study examined how technology readiness shapes employees' appraisal of generative AI (GenAI) as a job resource or a job demand, and how these appraisals translate into performance in SMEs. Beyond supporting established JD–R mechanisms, the findings offer several insights that extend current research on AI in the workplace.

First, the results reveal an asymmetric role of technology readiness dimensions, challenging the assumption that positive dispositions uniformly generate beneficial outcomes. While optimism enhances AI-related job resources, innovativeness is associated with higher job demands. This suggests that innovative employees do not simply benefit more from GenAI but engage more intensively with it, thereby encountering greater complexity, validation effort and cognitive load. This finding refines TRI by showing that proactive technology orientations may increase exposure to strain in AI-enabled work, extending prior work on technology readiness (Parasuraman and Colby, 2015) and responding to recent calls to better understand employee–AI interaction dynamics (Zirar *et al.*, 2023).

Second, the findings nuance the "double-edged sword" view of AI (Liang *et al.*, 2022; Scholze and Hecker, 2024). Rather than balanced positive and negative effects, the results indicate a systematic asymmetry: resource creation is driven by a single factor (optimism), whereas multiple factors (innovativeness, insecurity, discomfort) contribute to demand amplification. This suggests that AI-related demands may be more structurally pervasive than its resource benefits, particularly in early-stage or resource-constrained contexts such as SMEs (Sultan and Riyadh, 2025).

Third, while the JD–R dual-pathway logic is supported (Bakker *et al.*, 2023), the results challenge the assumption that strain directly undermines performance. Exhaustion does not significantly affect performance once engagement is considered. Instead, performance is primarily driven by the motivational pathway, with exhaustion influencing performance indirectly through its effect on engagement. This aligns with prior evidence emphasizing the central role of engagement in performance outcomes (Costa *et al.*, 2015; Zeijen *et al.*, 2020) and suggests that resource-enabled motivation is more critical than strain reduction alone in AI-enabled work contexts.

Fourth, the SME context emerges as a critical boundary condition. The stronger effects observed in smaller firms indicate that AI-related demands and resources have more direct and amplified consequences when organizational buffers are limited. This is consistent with research showing that SMEs rely more heavily on individual capabilities and exhibit lower levels of formalization and structural support (Kotey and Slade, 2005; Thong, 1999). The findings therefore extend JD–R research by demonstrating that demand–resource dynamics are not only task-dependent but also contingent on organizational structure, particularly firm size.

Overall, the study contributes by positioning technology readiness as a distal antecedent of AI-specific job appraisals, demonstrating that GenAI operates through asymmetric demand–resource mechanisms and showing that performance in AI-enabled contexts is primarily driven by engagement rather than strain avoidance, thereby advancing recent research on AI-related work experiences (Scholze and Hecker, 2024; Zhou *et al.*, 2024).

5.2 Practical implications

The findings offer clear, actionable implications for SME managers implementing generative AI.

First, GenAI implementation should be actively designed rather than passively adopted. Because AI can function as both a resource and a demand, managers should reduce unnecessary cognitive load by simplifying validation procedures, clarifying responsibility for AI-assisted decisions and minimizing redundant oversight tasks. This is particularly important given evidence that AI-related demands can increase exhaustion and withdrawal behaviors (Teng *et al.*, 2024; Nguyen and Nguyen, 2025).

Second, training initiatives should prioritize effective use over basic adoption. Given that engagement drives performance, training should focus on how GenAI supports task execution – such as prompt design, output evaluation and workflow integration – rather than solely on technical functionality. This aligns with research highlighting the importance of meaningful and supportive work experiences in enhancing engagement (Blustein *et al.*, 2023).

Third, managers should carefully manage highly innovative employees. Although often seen as natural AI champions, these individuals may experience higher job demands due to deeper engagement with the technology. Providing structured support, dedicated experimentation time and clear usage boundaries can prevent overload.

Fourth, SMEs should implement lightweight AI governance mechanisms. Even simple practices – defining when outputs require verification, establishing usage guidelines and clarifying accountability – can reduce uncertainty and perceived demands, particularly among employees with higher insecurity or discomfort (Zhang and Soderberg, 2026).

Finally, given that effects are stronger in smaller firms, managers should recognize that individual experiences with GenAI translate directly into organizational performance. This reflects broader evidence that SME performance is highly sensitive to employee-level processes and capabilities (Sparrow and Cooper, 2014).

5.3 Limitations and future research directions

Several limitations warrant consideration. First, the cross-sectional design limits causal inference. Although grounded in the JD–R framework, reciprocal relationships between engagement and AI appraisals cannot be excluded. Longitudinal designs would allow examination of how these relationships evolve over time and capture potential dynamic interactions between job demands, resources and employee outcomes.

Second, all variables were measured using self-reports, raising potential common method concerns. While validity tests indicate satisfactory discriminant properties, future studies should incorporate objective performance indicators or supervisor evaluations.

Third, the sample is restricted to UK-based SME employees who already use GenAI regularly. The findings, therefore, reflect post-adoption experiences and may not generalize to non-users, large organizations or different national contexts.

Finally, task-level characteristics were not explicitly modeled. Variables such as task complexity, interdependence or decision criticality may further condition AI-related demand and resource perceptions.

Future research could extend this work in several ways. Longitudinal and diary studies could examine how AI-related resources and demands evolve over time. Multilevel designs may explore how individual appraisals aggregate into team- or firm-level outcomes, particularly in SMEs where individual behavior has disproportionate impact.

Additional boundary conditions should be examined, including AI governance maturity, leadership support, digital self-efficacy and trust calibration. Expanding outcome variables beyond performance – such as creativity, knowledge sharing, ethical decision-making or turnover intentions – would further illuminate GenAI's organizational consequences.

As regulatory frameworks and AI capabilities continue to evolve, comparative research across industries and national contexts will be essential for assessing the stability of the motivational and strain pathways identified here.

Finally, future research could extend this work to the adoption of agentic artificial intelligence in SMEs, examining challenges related to autonomy, control and trust and the organizational mechanisms needed for its effective integration into work processes.

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