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Managing Technostress in Digital Workplaces: The Role of Digital Employee Experience within the Job Demands–Resources Framework

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Abstract. In digitally intensive work environments, organizations increasingly rely on advanced technologies to enhance efficiency and service performance, yet such transformations often generate unintended employee strain. Drawing on the Job Demands–Resources (JD-R) model, this study examines digital employee experience (DEX) as a strategic digital job resource and investigates its effects on technostress, burnout, turnover intention, and job performance. Survey data were collected from 412 employees working in technology-oriented firms in Vietnam and analyzed using partial least squares structural equation modeling (PLS-SEM). The results show that DEX significantly reduces technostress and burnout. Technostress further acts as a key mediating mechanism linking DEX to burnout, indicating that poor digital experiences accelerate resource depletion and psychological strain. Burnout, in turn, increases turnover intention and undermines job performance. By conceptualizing DEX as a multidimensional digital job resource encompassing technical enablement, inclusiveness, and cohesiveness, this study extends the JD-R framework to digitally mediated work settings. The findings offer important theoretical and managerial insights for designing digital work systems that mitigate technostress and sustain employee performance in technology-intensive service contexts.

Keywords: Digital employee experience; Technostress; Job Demands–Resources model; Digital workplace; Burnout; Job performance; Turnover intention; Digital work systems.

1. Introduction

In recent years, organisations have faced a global productivity challenge. While financial constraints partly explain this trend, the accelerating pace of digital transformation has played a more influential role in reshaping productivity dynamics (Li et al., 2022). The widespread adoption of digital tools has changed how employees perform their work, requiring both employees and organisations to adapt to new work-related demands. Accordingly, this transformation necessitates the development of revised managerial approaches aimed at sustaining employee productivity in increasingly digital work environments (Oludapo et al., 2024).

Existing studies suggest that digital transformation can enhance organisational performance by fostering innovation, improving information flows and strengthening competitive advantage (Goraya et al., 2024; Zhang et al., 2023). However, other research presents a less optimistic view, reporting that over 80% of digital transformation initiatives fail to achieve their intended outcomes due to limited managerial readiness, weak strategic alignment and the persistent assumption that technology alone is sufficient to drive success (Oludapo et al., 2024). These contrasting findings suggest that digital transformation goes beyond technological adoption and involves a complex organisational change process shaped by human and behavioural factors.

Recognising this, scholars increasingly argue that digital transformation is fundamentally a human transformation, as its success depends on employees' capacity to adapt to and effectively engage with evolving digital systems (Oludapo et al., 2024). Employees therefore become central actors in digital transformation and organisations are unlikely to achieve sustainable productivity or deliver superior customer experiences without deliberate investment in workforce development and employee well-being (Goraya et al., 2024).

This growing emphasis has elevated employee experience as a central concept in contemporary human resource management. Employee experience refers to employees' holistic perceptions of their interactions with organisational systems, processes, and stakeholders, which in turn shape their motivation and performance (Başar, 2024). Prior research indicates that positive workplace experiences foster a sense of belonging, enhance motivation, and improve productivity, particularly among younger generations (Cornelius et al., 2022). As workplaces become increasingly digitalised, this concept has evolved into digital employee experience, which focuses on how digital platforms, AI-enabled systems and collaborative technologies influence employees' day-to-day work experiences (Gheidar & ShamiZanjani, 2020).

The rise of hybrid work models has further heightened the relevance of digital employee experience. Accelerated by the COVID-19 pandemic, hybrid work arrangements offer greater flexibility and autonomy, yet they also blur work–life boundaries and introduce risks such as social isolation and burnout (Lemonaki et al., 2021). In these contexts, employees increasingly depend on digital systems and experience management platforms to sustain collaboration, productivity, and engagement (Porkodi et al., 2023).

However, this intensive reliance on digital technologies also heightens employees vulnerability to technostress, defined as a form of psychological strain arising from individuals' difficulties in coping with information and communication technology (ICT) demands (Tarafdar et al., 2007). Contemporary perspectives further conceptualise technostress as encompassing physical, emotional and behavioural strain arising from rapid technological change, including: techno-overload, techno-invasion, techno-complexity, techno-insecurity and techno-uncertainty. Collectively, these stressors may erode employee well-being and adversely affect work performance.

The interaction between digital employee experience and technostress is particularly salient in technology-intensive industries where digital systems underpin everyday work processes. Although intelligent digital tools and AI-enabled HR systems can enhance employee engagement and support talent development (Porkodi et al., 2023), these technologies may also increase cognitive demands and uncertainty, thereby heightening technostress and the risk of burnout. This duality highlights the relevance of the JD-R model, which offers a useful framework for explaining how job resources (digital employee experience) can mitigate the adverse effects of job demands (technostress) on employee well-being and performance (Wang et al., 2023).

Against this backdrop, the present study examines the relationship between digital employee experience and technostress among employees working in technology firms in Vietnam. Drawing on an extended JD-R framework, the study aims to provide a more understanding of how digital work environments influence employee well-being and productivity.

Following this introduction, the second section presents the framework and hypothesis development. The third section describes the research methodology, followed by empirical results in the fourth section. The fifth section discusses the findings and the final section concludes by presenting the implications, limitations and directions for future research.

2. Literature Review

2.1. Digital Employee Experience (DEX)

The conceptualisation of DEX has evolved from an initial technology-centric focus on usability, accessibility, and system reliability toward a more holistic and psychologically informed perspective (Başar, 2024; DeLone & McLean, 2003). Early studies primarily emphasised digital tools as system-quality attributes, whereas subsequent research broadened the concept to include organisational and individual factors such as culture, leadership and career development opportunities (Gheidar & ShamiZanjani, 2021; Moganadas & Goh, 2022). In parallel, another stream of research has conceptualised DEX in terms of socio-psychological outcomes, highlighting dimensions such as inclusiveness and cohesiveness that reflect employees sense of value, belonging and quality of digital collaboration (Bhatti et al., 2024; Cornelius et al., 2022).

However, this socio-psychological perspective may understate the foundational role of technical systems as enablers of positive digital work experiences. To reconcile these perspectives, the present study conceptualises DEX as a reflective second-order construct comprising: Inclusiveness, Cohesiveness and Technical Enablement. This integrative conceptualisation captures both the socio-psychological and technical dimensions of digital work environments (DeLone & McLean, 2003; Gheidar & ShamiZanjani, 2021; Moganadas & Goh, 2022). Importantly, this approach acknowledges that deficiencies in either dimension may transform digital systems from supportive job resources into sources of strain, thereby contributing to adverse outcomes such as technostress and burnout (Boccoli et al., 2023; Ibrahim Hassan et al., 2024).

2.2. Technostress (TS)

Within the organisational and information systems literature, technostress is commonly defined as the stress experienced by end users as a result of their interaction with information and communication technologies (ICTs). Seminal work by Tarafdar et al. (2007), whose framework is adopted in the present study, conceptualises technostress through five core dimensions, widely referred to as “technostress creators”. These dimensions include: techno-overload, which reflects being required to work faster and longer; techno-invasion, which captures the blurring of work–life boundaries; techno-complexity, referring to feelings of inadequacy arising from the complexity of ICTs; techno-insecurity, which denotes concerns about job displacement due to technological advances; and techno-uncertainty, representing stress associated with frequent technological changes and updates (Tarafdar et al., 2015; Tarafdar et al., 2007).

Extensive empirical evidence indicates that technostress creators are associated with a range of adverse work outcomes, including reduced job satisfaction and lower organisational commitment (Nisafani et al., 2020; Ragu-Nathan et al., 2008), as well as impaired employee performance (Tarafdar et al., 2015; Tarafdar et al., 2010). In particular, technostress has been consistently linked to emotional exhaustion and burnout, especially within digitally intensive work environments (Maslach & Jackson, 1981; Nisafani et al., 2020; To et al., 2024).

From this perspective, technostress can be conceptualised as a key psychological mechanism through which the quality of digital employee experience translates into employee strain. When digital systems are insufficiently aligned with employees capabilities or impose excessive demands, they may intensify stress responses and increase the risk of burnout. This reasoning underscores the importance of examining digital employee experience, technostress and burnout within an integrated theoretical framework.

2.3. Burnout (BO)

Burnout is a psychological syndrome arising from prolonged exposure to job-related stress and is characterised by emotional and physical exhaustion (Wang et al., 2023). Traditionally, burnout has been conceptualised as comprising emotional exhaustion, depersonalisation, and reduced personal accomplishment (Maslach & Jackson, 1981). More recent work further suggests that these dimensions reflect a broader loss of meaning and motivation at work (Maslach & Leiter, 2016).

Consistent with the JD-R model, the present study conceptualises burnout through two core dimensions: exhaustion and disengagement, which are widely regarded as universal indicators of strain across occupational contexts (Demerouti et al., 2001). Exhaustion refers to the depletion of emotional and cognitive resources resulting from sustained job demands, whereas disengagement reflects psychological withdrawal from work, including detachment from technology-mediated tasks (Bakker et al., 2002). In digital work environments, persistent technological demands, such as frequent system updates, constant connectivity and high cognitive load, can intensify exhaustion and foster disengagement. Accordingly, burnout represents a critical outcome through which technostress transmits the detrimental effects of poor DEX on employee well-being and performance.

2.4. Turnover Intention (TI)

Turnover intention refers to an employee's deliberate and conscious decision to leave the organisation and represents the final stage of the withdrawal cognition process (Mobley, 1982). It reflects a cognitive state in which employees consider and plan to resign from their current job (Tett & Meyer, 1993). Although turnover intention is typically treated as a unidimensional construct, it encompasses both cognitive and motivational aspects of employees decision-making processes (Lu et al., 2023).

From a JD-R perspective, turnover intention can be understood as a motivational outcome that emerges when prolonged work-related stress and insufficient resources undermine employee engagement and satisfaction. In digitalised work environments, inadequate technical support, information overload and ineffective communication through digital channels may intensify work-related stress, thereby increasing employees intentions to quit. Conversely, when employees experience strong digital support and seamless technological integration, their sense of control and perceived availability of job resources are enhanced. A positive DEX can therefore reduce turnover intention by fostering engagement and job satisfaction. Given the central role of technology in contemporary organisations, examining turnover intention through the lens of DEX provides valuable insights into how digital working conditions influence employee retention and organisational stability (Lu et al., 2023).

2.5. Job Performance (JP)

Job performance refers to the extent to which employees effectively fulfil their job responsibilities and contribute to organisational objectives (Campbell, 1990). It is commonly examined through two dimensions: task performance the efficient execution of core job duties and contextual performance voluntary behaviours that support the social and organizational environment (Porkodi et al., 2023).

Within the JD-R model, job performance represents a positive motivational outcome that emerges when employees possess sufficient resources to manage job demands.

In digital workplaces, such resources include intuitive systems, accessible information and effective collaboration tools. High-quality digital experiences enable employees to work more efficiently, adapt to changing task requirements, and sustain engagement (Vaziri et al., 2022). Accordingly, job performance serves as a key outcome through which DEX translates into meaningful organizational benefits. A supportive digital environment strengthens employees psychological resources and operational effectiveness, reinforcing a cycle of engagement and productivity (Vaziri et al., 2022). Thus, assessing job performance helps clarify the strategic value of DEX as both an experiential and performance-enhancing construct.

2.6. Job Demands–Resources model (JD-R model)

The JD-R model, proposed by Demerouti et al. (2001) and further developed by Bakker and Demerouti (2017), explains how job demands and job resources shape employee well-being and performance through health-impairment and motivational processes. Originally developed for traditional work contexts, the JD-R model conceptualized demands mainly as workload or emotional strain and resources as organizational, social, or task-related supports.

However, in digitally mediated workplaces, both demands and resources are increasingly embedded in employees' daily interactions with digital systems. Digital work introduces distinct demands such as technostress arising from system complexity, constant connectivity, and rapid technological change, while digital resources depend not only on availability but also on the quality of employees' digital experiences. Accordingly, this study refines the JD-R framework by positioning DEX as a multidimensional digital job resource and TS as a central digital job demand, thereby extending the model to better capture the socio-technical nature of contemporary digital work environments.

2.7. Conservation of Resources theory (COR theory)

COR theory posits that stress and burnout arise when individuals experience actual or threatened loss of valued resources, such as time, energy, and social support, or when they fail to gain expected resources (Hobfoll, 1989, 2001). While COR theory was initially applied to physical, social, and psychological resources, it is particularly relevant for digital work contexts where resources are increasingly embedded in technology-mediated environments. Digital resources differ from traditional organizational resources in that they are more vulnerable to rapid depletion and sudden failure, as system breakdowns, constant interruptions, and continuous connectivity can quickly exhaust employees' cognitive and emotional resources. From this perspective, TS represents a mechanism of accelerated resource loss in digital workplaces, whereas a high-quality DEX constitutes a protective resource pool that helps preserve employees' resources and interrupt loss cycles. Integrating COR theory with the JD-R framework, therefore, provides a deeper explanation of why deficiencies in DEX amplify BO through TS in highly digitalized work settings.

2.8. Self-determination theory (SDT theory)

SDT, originating from Deci and Ryan's foundational work (1980), has become a leading framework for understanding human motivation. SDT posits that individuals possess three universal psychological needs: autonomy, competence, and relatedness, whose satisfaction determines whether motivation is experienced as autonomous or controlled (Manganelli et al., 2018; Ryan & Deci, 2000). When these needs are fulfilled, individuals exhibit greater well-being, higher performance, and reduced burnout (Manganelli et al., 2018). Conversely, need frustration fosters controlled motivation and is associated with poorer performance, psychological strain, and increased turnover intentions (Gautam & Gautam, 2024).

Recent scholarship extends SDT to digital work environments, arguing that systems and technologies should be designed to support autonomy, enhance competence, and facilitate relatedness to promote motivation and well-being (Cornelius et al., 2022). Accordingly, SDT provides a robust framework for understanding how features of the digital and organizational climate can either enable optimal psychological functioning or give rise to maladaptive outcomes such as stress and disengagement.

2.9. The direct effect of Digital employee experience on Burnout and Technostress

In contemporary digital workplaces, the quality of employees' technological interactions conceptualized as DEX has emerged as a critical determinant of employee well-being. Drawing on the JD-R model, DEX can be understood as a key digital job resource that enables employees to achieve work goals efficiently while conserving personal resources such as time and cognitive energy. A high-quality DEX extends beyond the mere availability of digital technologies to include seamlessly integrated systems, intuitive user interfaces that reduce cognitive load, and reliable technological support. In contrast, a poor DEX characterized by system inefficiencies, inadequate training, and technological friction represents a lack of resources that compels employees to expend additional effort to cope with digital demands. From a COR perspective, such resource depletion increases emotional exhaustion, a core component of burnout (Hobfoll, 2001).

Empirical evidence supports this resource-based argument. Prior studies have shown that deficiencies in digital resources and fluency are associated with higher levels of exhaustion and deteriorating mental health (Moganadas & Goh, 2022), while interventions that optimize digital work environments can effectively mitigate burnout (Thomas Craig et al., 2021). Accordingly, by functioning as a protective digital resource, a higher-quality DEX is expected to reduce employee burnout. Based on this reasoning, the following hypothesis is proposed:

H1: Digital employee experience has a negative effect on Burnout.

The significance of DEX has increased substantially in modern organizations, particularly in the post-pandemic era (Porkodi et al., 2023). According to Moganadas and Goh (2022), DEX encompasses multiple dimensions, including technological infrastructure, workplace environment, organizational culture, and employee-related factors. Extending this perspective, Gheidar and Zanjani (2021) identify eight interconnected components such as leadership practices, strategic alignment, and cultural adaptability, highlighting that DEX represents a holistic framework influencing how employees interact with digital systems and organizational processes.

On the other hand, technostress refers to a unique form of stress that emerges from challenges associated with technology adoption and continuous digital change, making it distinct from general occupational stress (Tarafdar et al., 2015). This stress reaction is often manifested through symptoms like mental fatigue, reduced self-efficacy, anxiety, and increased scepticism, which ultimately contribute to work strain. (Wang et al., 2023). Over time, technostress can shift from a temporary discomfort into a chronic psychological burden, particularly when employees struggle with constant updates or complex systems (Tarafdar et al., 2010). Empirical evidence suggests that employees exposed to a poor digital work environment such as unreliable systems, insufficient support, and escalating digital demands are more prone to technostress (Goraya et al., 2024). Conversely, a positive DEX characterized by intuitive systems, adequate digital resources, and effective training can mitigate these stressors by reducing uncertainty and perceived complexity. On that basis, hypothesis H2 is formulated as follows:

H2: Digital employee experience has a negative effect on Technostress.

2.10. The mediating role of Technostress in the relation between Digital employee experience and Burnout.

The relationship between technostress and burnout remains debated, as empirical evidence on the direct link between ICT use and BO is still inconclusive (Tarafdar et al., 2015). BO is commonly conceptualized as a gradual depletion of energy under prolonged stress and can emerge at different career stages, often accompanied by adverse health outcomes (Maslach & Jackson, 1981; Maslach & Leiter, 2016). Prior research emphasizes emotional exhaustion as the core component of burnout, with other dimensions such as reduced accomplishment and depersonalization considered secondary (Maslach & Leiter, 2016). Accordingly, the present study focuses on emotional exhaustion as the primary manifestation of burnout. Continuous exposure to technostressors including techno-overload, techno-complexity, techno-insecurity, techno-uncertainty, and techno-invasion can erode work–life boundaries and deplete social and psychological resources, thereby intensifying stress and reducing job-related efficiency (Snyder et al., 2020; Tarafdar et al., 2007; Thomas Craig et al., 2021). Based on this reasoning, the following hypothesis is proposed:

H3: Technostress has a positive effect on Burnout.

The increasing integration of digital technologies has intensified employees' exposure to TS, defined as the psychological strain arising from the use or anticipated use of new technologies (Tarafdar et al., 2007). DEX reflects employees' holistic perceptions of their digital work environment, encompassing technological systems, communication, managerial support, and organizational culture (Gheidar & ShamiZanjani, 2020). When digital experiences are poorly designed or insufficiently supported, employees are more likely to experience technostress, characterized by anxiety, cognitive overload, and reduced self-efficacy. Persistent exposure to technology-related stressors such as techno-overload, techno-complexity, and techno-insecurity can deplete emotional and cognitive resources and increase BO risk (Maslach & Leiter, 2016; Ragu-Nathan et al., 2008), consistent with the JD-R model's assertion that excessive demands without adequate resources culminate in strain (Bakker & Demerouti, 2017; Bakker et al., 2002). Although prior research has established a direct link between technostress and burnout, the broader mechanism linking DEX, TS, and BO remains underexplored. Addressing this gap, the present study conceptualizes technostress as a mediating mechanism through which digital employee experience shapes burnout, such that poor DEX amplifies technostress and burnout, whereas supportive digital environments mitigate strain by enhancing employees' resources and digital efficacy..

H4: Technostress plays a mediating role in the relationship between Digital Employee Experience and Burnout.

2.11. The direct effect of Burnout on Turnover intention and Job performance

Burnout, defined as a psychological syndrome arising from prolonged exposure to job stressors that results in exhaustion and disengagement (Demerouti et al., 2001), is a central predictor of employees' intention to leave the organization. This relationship is well explained by COR theory, which posits that burnout reflects severe depletion of emotional and cognitive resources (Hobfoll, 1989, 2001). When employees experience exhaustion and reduced involvement, turnover intention functions as a coping strategy aimed at preventing further resource loss by withdrawing from the demanding environment (Park & Min, 2020). Extensive empirical evidence reinforces this mechanism. A meta-analysis in the service sector demonstrated that emotional exhaustion and depersonalization exert strong positive effects on turnover intention (Park & Min, 2020), and recent studies continue to support this direct association (Gautam & Gautam, 2024). Guided by this theoretical and empirical foundation, the following hypothesis is proposed:

H5: Burnout has a positive effect on Turnover intention.

Further, burnout undermines job performance through two core mechanisms aligned with its dimensions of exhaustion and disengagement. From a COR perspective, exhaustion reflects severe depletion of energy and cognitive resources, impairing functions such as working memory and problem-solving, and increasing errors in task execution (Hobfoll, 2001; Lemonaki et al., 2021). From a SDT perspective, disengagement indicates motivational erosion caused by unmet needs for autonomy, competence, and relatedness (Deci & Ryan, 2008), resulting in reduced effort, withdrawal, and diminished task proficiency. Empirical studies consistently support this dual mechanism: burnout especially exhaustion is negatively associated with in-role job performance (Taris, 2006), and meta-analyses show that burnout elevates the risk of mistakes and adverse events (Lemonaki et al., 2021). Therefore, based on the combined effects of resource depletion and motivational withdrawal, the following hypothesis is proposed:

H6: Burnout has a negative effect on Job performance.

3. Research Methodology

Data were collected through an online survey administered to employees working in technology-oriented firms in Vietnam, particularly in the IT and Fintech sectors. Using a convenience sampling approach, participants were recruited through professional networks, online industry forums and social media platforms commonly used by IT and Fintech professionals (LinkedIn and Facebook professional groups). A total of 433 responses were obtained, of which 412 valid cases were retained after data screening. The sample is predominantly composed of early–career employers, with 82% of respondents aged 18–28 and 74.5% having less than three years of work experience, reflecting a digitally native workforce commonly found in technology-intensive industries. Most respondents worked under online (47.8%) or hybrid (36.9%) arrangements and held full-time positions (74.5%). While this demographic profile is suitable for examining DEX and TS in digital workplaces, it may limit the generalizability of the findings beyond early-career employees. In addition, the survey employed a convenience sampling method.

The dataset was analyzed using the PLS-SEM method with SmartPLS 3.0. The analysis followed the recommended two-step approach: evaluating the measurement model and then assessing the structural model. Reliability was measured using cronbach's alpha and composite reliability, while convergent validity was assessed through AVE. Discriminant validity was examined using the HTMT criterion. To test the significance of loadings and structural paths, the study employed a bootstrapping procedure with 5,000 resamples using the bias-corrected method. Collinearity issues were checked through VIF values, all of which were below recommended thresholds.

All constructs were measured using multi-item reflective scales on a five-point Likert format. DEX was conceptualized as a second-order reflective construct comprising three first-order dimensions: Inclusiveness, Cohesiveness and Technical Enablement. The measurement items for these dimensions were adapted from established literature on inclusiveness (Shore et al., 2011), interpersonal cohesion and trust (McAllister, 1995), and information systems success and system quality (DeLone & McLean, 2003). TS is constructed by Tarafdar et al. (2015), including 12 items representing five technostress creators: Techno-overload, Techno-invasion, Techno-complexity, Techno-insecurity, and Techno-uncertainty. BO was measured by Demerouti et al. (2001) using six items capturing exhaustion and disengagement, while TI and JP were measured using four items each by Lu et al. (2023) and Vaziri et al. (2022). All measurement items are reported in full in Appendix A to allow readers to directly assess content validity and construct coverage.

3.1. Measurement model

The measurement model was assessed using a two-stage approach to accommodate the hierarchical nature of the constructs, following the recommendations of Hair et al. (2020). The first step involved evaluating the reliability and validity of the lower-order constructs, followed by an assessment of the higher-order constructs. The primary criteria for evaluation included internal consistency reliability, convergent validity and discriminant validity.

3.1.1. Lower-Order measurement model

3.1.1.1. Reliability and Convergent validity.

The assessment began by examining the reliability and convergent validity of the first-order reflective constructs. As presented in Table 1, all indicator outer loadings were above the recommended threshold of 0.70, with values ranging from 0.752 to 1.000, indicating that the indicators are strong representatives of their respective latent constructs (Hair Jr et al., 2020).

Internal consistency reliability was evaluated using composite reliability and cronbach's alpha. The CR values for all constructs, which ranged from 0.876 to 1.000, surpassed the 0.70 benchmark, demonstrating robust internal consistency (Cheung et al., 2024). Similarly, cronbach's alpha values were all above 0.769, exceeding the recommended threshold of 0.70 (Cheung et al., 2024), further supporting the reliability of the scales. Convergent validity was confirmed by examining the average variance extracted. The AVE values for all latent variables were greater than the minimum threshold of 0.50, ranging from 0.678 to 1.000. This indicates that, on average, each construct explains more than half of the variance of its indicators (Haudi et al., 2022). These results provide strong evidence for the reliability and convergent validity of the lower-order measurement model.

3.1.1.2. Discriminant validity

To assess discriminant validity, the heterotrait-monotrait ratio of correlations (HTMT) was employed, as it is considered a more stringent criterion than traditional methods (Sarstedt et al., 2021). As shown in Table 2, all HTMT values were below the conservative threshold of 0.85 (Sarstedt et al., 2021), with the highest observed value being 0.800 (between TIN and TC). Although this value is relatively close to the recommended cutoff, such proximity is theoretically expected, as both constructs reflect distinct yet related facets of technology-induced strain. Techno-invasion captures the blurring of work–life boundaries caused by constant connectivity, whereas techno-complexity reflects cognitive overload arising from the perceived difficulty of digital systems. Consistent with prior technostress research (Tarafdar et al., 2007; Ragu-Nathan et al., 2008), these dimensions are conceptually distinct and were therefore retained as separate constructs. Furthermore, all indicators loaded highest on their intended constructs, and no problematic cross-loadings were observed. Taken together, these results provide adequate support for discriminant validity.

3.1.2. Higher-Order measurement model

Two higher-order constructs: DEX and TS, were specified and assessed using the repeated indicators approach (Hair Jr et al., 2020). DEX was modeled as a second-order reflective construct comprising Cohesiveness, Inclusiveness and Technical Enablement, with substantial loadings ranging from 0.865 to 0.881, strong internal consistency reliability (CR = 0.904), and adequate convergent validity (AVE = 0.758) (Hair Jr et al., 2020; Sarstedt et al., 2021). Similarly, TS was conceptualized as a higher-order construct consisting of five dimensions (TC, TIN, TINS, TO and TU), showing loadings between 0.785 and 0.863, a composite reliability of 0.909, and an AVE of 0.667 (Sarstedt et al., 2021). Discriminant validity was further confirmed using the HTMT criterion, with all values below the recommended 0.85 threshold, supporting the distinctiveness of DEX and TS (Sarstedt et al., 2021).

3.2. Structural model

Following the confirmation of the measurement model's reliability and validity, the structural model was assessed. The analysis involved examining collinearity issues, testing the significance of path coefficients for the direct and indirect relationships, and evaluating the model's explanatory power. Prior to examining the structural relationships, the overall model fit was assessed using global fit indices recommended for PLS-SEM. The results indicate an acceptable overall model fit (SRMR = 0.055; NFI = 0.895), while RMS_theta (0.133) was slightly above the recommended threshold, a pattern commonly observed in complex models with higher-order constructs (Sarstedt et al., 2021). Next, the structural model was assessed for collinearity among predictor constructs. As shown in Table 5, all Variance Inflation Factor (VIF) values ranged from 1.000 to 1.342, falling well below the conservative 3.0

threshold and indicating that multicollinearity was not a concern (Hair Jr et al., 2020). Given that all data were collected from a single source, common method bias was further assessed using the full collinearity approach, and all VIF values were below the recommended threshold of 3.3, indicating that common method bias is unlikely to confound the results. Overall, these findings demonstrate that the measurement model meets established standards of reliability and validity, providing a robust foundation for subsequent structural equation modeling.

The significance of the direct relationships was tested using a bootstrapping procedure with 5,000 resamples. The results, summarized in Table 5, indicate that all five direct hypotheses (H1, H2, H3, H5, and H6) were statistically supported at $p < 0.001$ level. Specifically, DEX was found to have a significant negative effect on both TS ($\beta = -0.505$, $t = 12.273$) and BO ($\beta = -0.260$, $t = 5.318$), supporting H2 and H1, respectively. The path from TS to BO was positive and significant ($\beta = 0.431$, $t = 8.092$), confirming H3. Furthermore, BO demonstrated a significant positive impact on TI ($\beta = 0.686$, $t = 18.604$) and a significant negative impact on JP ($\beta = -0.553$, $t = 15.267$), thus supporting H5 and H6.

The model's explanatory power (R^2_{adj}) was substantial, explaining 25.3% of the variance in TS, 36.4% in BO, 46.9% in TI, and 30.4% in JP. While these R^2 values are comparable to those reported in prior organizational and information systems research, they also indicate that multiple factors beyond DEX influence TS and BO. Prior studies suggest that individual differences (e.g., technology self-efficacy), workload, and organizational support may further explain variance in these outcomes. Accordingly, future research may extend the model by incorporating additional predictors to enhance explanatory power. The effect size (f^2) analysis indicated a medium-to-large effect of DEX on TS ($f^2 = 0.342$), a medium effect of TS on BO ($f^2 = 0.219$), and a small effect of DEX on BO (($f^2 = 0.080$). Notably, BO exerted large effects on both JP ($f^2 = 0.440$) and, most substantially, on TI ($f^2 = 0.889$) (Sarstedt et al., 2021).

Finally, the mediating role of TS in the relationship between DEX and BO was examined. As detailed in Table 5, the analysis confirmed a significant indirect effect of DEX on BO via TS ($\beta = -0.218$, $t = 7.020$, $p < 0.001$). This result supports H4, indicating that TS acts as a significant intermediary mechanism through which DEX influences BO.

4. Discussion

A central theoretical contribution of this study is the extension of the JD-R model into the digital workplace by positioning DEX as a critical digital job resource. Earlier research tended to conceptualize DEX in a narrow manner, either emphasizing technological attributes such as system quality (Başar, 2024; DeLone & McLean, 2003) or socio-psychological dimensions such as inclusiveness and cohesiveness (Bhatti et al., 2024; Cornelius et al., 2022). By integrating these perspectives into a reflective second-order construct consisting of technical enablement, inclusiveness and cohesiveness, this study offers a more holistic representation of how employees experience digital environments (Gheidar & ShamiZanjani, 2021; Moganadas & Goh, 2022).

The structural model results provide strong empirical support for this conceptualization. DEX demonstrated a substantial negative relationship with technostress ($\beta = -0.505$, $p < 0.001$) and a significant negative relationship with burnout ($\beta = -0.260$, $p < 0.001$). These findings reinforce the JD-R argument that high-quality digital resources alleviate digital demands and protect employees from strain (Bakker & Demerouti, 2017; Wang et al., 2023). They also correspond with evidence showing that organizational interventions aimed at improving digital systems effectively reduce burnout (Thomas Craig et al., 2021).

A major theoretical insight emerges from the mediating role of technostress. As expected, technostress was positively associated with burnout ($\beta = 0.431$, $p < 0.001$) and significantly mediated the relationship between DEX and burnout (indirect effect $\beta = -0.218$, $p < 0.001$). This mediation is well explained by COR theory: when employees face poor digital environments, they must expend additional emotional and cognitive resources to compensate; technostress accelerates this loss, eventually culminating in burnout (Hobfoll, 2001; Ragu-Nathan et al., 2008).

The consequences of burnout were also evident. Burnout strongly increased TI ($\beta = 0.686$, $p < 0.001$), reflecting consistent findings that exhausted and disengaged employees are more likely to consider leaving their organizations (Gautam & Gautam, 2024; Park & Min, 2020). Burnout also had a marked negative effect on job performance ($\beta = -0.553$, $p < 0.001$), consistent with evidence that resource depletion impairs cognitive functioning and erodes motivation (Deci & Ryan, 2008; Hobfoll, 2001; Lemonaki et al., 2021).

These findings suggest a coherent process in which higher-quality DEX is associated with lower technostress, which in turn is linked to reduced burnout, ultimately contributing to lower turnover intention and enhanced job performance. From a theoretical perspective, the results help clarify how digital job resources and digital job demands interact within the JD-R and COR theoretical frameworks. From a practical standpoint, the findings highlight the strategic importance of cultivating a high-quality DEX. Organisations should prioritise user-centric and reliable digital systems (technical enablement), foster collaborative and cohesive digital interactions, and promote inclusiveness in digital work processes. These efforts are particularly important in fast-moving sectors such as IT and Fintech, where digital complexity is high, and employee well-being is critical to sustaining performance.

5. Conclusion and Limitations

5.1 Conclusion

This study contributes to the literature on employee well-being in digital workplaces by refining the JD-R model rather than merely applying it to a new empirical context. By conceptualizing DEX as a multidimensional digital job resource that integrates technical enablement, inclusiveness and cohesiveness, the study extends the JD-R framework to better capture the socio-technical nature of contemporary digital work environments.

More importantly, the findings advance JD-R theory by identifying technostress as a central psychological mechanism through which digital job resources influence employee well-being. While prior JD-R research often conceptualizes job demands in broad terms, this study demonstrates that technostress represents a distinct form of digital demand that explains how deficiencies in digital employee experience translate into burnout. In doing so, the study refines the demand–strain pathway within the JD-R model, particularly in technology-intensive work settings.

By integrating this mechanism with insights from COR theory, the study further explains why poor digital environments accelerate resource depletion, whereas high-quality DEX helps preserve employees' cognitive and emotional resources. Thus, the contribution of this research lies not only in validating existing frameworks but in clarifying and extending their explanatory power in digitally mediated workplaces.

From a managerial perspective, the findings indicate that DEX should be managed as a strategic, multidimensional job resource rather than a generic outcome of digitalization. The three-dimensional DEX framework offers managers a practical diagnostic tool: deficiencies in technical enablement are likely to intensify techno-overload and techno-complexity, calling for user-centered system design and role-specific digital training; low digital inclusiveness may increase techno-insecurity and techno-uncertainty, highlighting the need for transparent communication and equitable access to digital tools; and weak digital cohesiveness requires interventions that strengthen social connection and psychological safety in digitally mediated collaboration rather than purely technical investments. These actions illustrate how managing DEX can function as a targeted digital wellness strategy that mitigates technostress and supports sustainable performance in highly digitalized work environments, particularly in IT and Fintech sectors.

5.2 Limitations and Future Research Directions

This study extends the JD-R Model to digital workplace contexts by conceptualizing DEX as a digital job resource that mitigates technostress and burnout, particularly among early-career digital workers. By focusing on GenZ employees in technology firms in Vietnam, the study provides generationally grounded insights into how digital natives perceive and manage technology-related demands; however, this focus also limits the generalizability of the findings to other age groups, industries, and cultural contexts. In addition, the cross-sectional and self-reported survey design restricts causal inference and may be subject to common method bias, suggesting that future studies should employ longitudinal designs, multi-source data, or marker-variable approaches to strengthen causal validity. Measurement-related limitations should also be acknowledged, as the technostress construct includes a single aggregated item for the techno-uncertainty dimension, which may not fully capture the evolving and multifaceted nature of uncertainty in contemporary digital work environments. While the sample size of 412 exceeds conventional statistical power requirements for PLS-SEM, future research could explicitly incorporate power analysis at the study design stage to further enhance methodological rigor. Building on these limitations, future studies should move beyond generic replication by examining theoretically meaningful extensions, such as the moderating roles of individual technology readiness and organizational culture, as well as differential effects of DEX dimensions across employee segments, job roles, and levels of digital intensity, thereby further refining the JD-R framework in digital settings.

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Appendix A.

Instrument Items

Digital Emloyee Experience (DEX): (DeLone & McLean, 2003; McAllister, 1995; Shore et al., 2011)

Inclusiveness - *DEX1:* In the digital working environment, I feel that I am treated with respect; *DEX2:* I feel free to express my opinions on digital platforms without worrying about negative consequences; *DEX3:* Managers use digital tools and data to make fair decisions about employees.

Cohesiveness - *DEX4*: Members of my team have a high level of trust in each other, even when collaborating in the digital workplace; *DEX5:* My colleagues are friendly and willing to support one another in interactions through digital platforms; *DEX6*: The members of my team get along well with each other during digital collaboration.

Technical Enablement - *DEX7*: The digital tools I use at work are easy to learn and use; *DEX8*: Our digital systems are reliable, and I receive timely support when issues occur; *DEX9*: Our digital tools integrate well with workflows and reduce unnecessary steps

Technostress (TS): (Tarafdar et al., 2015)

Techno-overload - *TS1:* The technologies I use at work force me to work much faster than before; *TS2:* The technologies I use increase my overall workload because of their complexity; *TS3:* I constantly have to change my work habits to adapt to new technologies.

Techno-invasion - *TS4:* Work-related technologies invade my personal life and reduce the time I can spend with family or personal activities; *TS5:* I have to sacrifice my vacation and weekend time to stay updated on new technologies; *TS6:* I feel my skills are inadequate to handle the complexity of the technologies required for my job; *TS7:* It takes me a long time to learn how to use new technologies effectively; *TS8:* I often feel overwhelmed by the complexity of the digital tools I am required to use.

Techno-insecurity - *TS9:* I feel a constant threat to my job security because of new technologies, *TS10:* I feel pressured to continuously update my technology skills to avoid being replaced. *TS11:* I feel threatened by coworkers who have more advanced technology skills than I do**.**

Techno-uncertainty - *TS12:* The constant introduction of new technologies, software, and system updates at my work makes me feel unsettled.

Burnout (BO): (Demerouti et al., 2001)

BO1: At times, I feel exhausted even before starting my tasks with digital systems; *BO2:* By the end of the day, I often feel completely fatigued from work and need a longer time to recover; *BO3:* While working, I frequently experience emotional exhaustion due to the continuous use of technology; *BO4:* I have begun to feel less engaged with the digital aspects of my work; *BO5:* I notice that I pay less attention to digital tasks and perform them in an almost robotic manner; *BO6:* I find myself complaining about my job more often, especially when it involves digital demands.

Turnover Intention (TI): (Lu et al., 2023)

TI1: I view my current role in the digital workplace as temporary rather than a long-term commitment; *TI2:* I intend to look for new job opportunities that provide a better digital experience or a healthier work–life balance; *TI3:* If I find another position with more advanced digital tools or less technological pressure, I would consider moving to that job; *TI4:* I have started searching for other job opportunities where the technology systems are easier to use and more supportive.

Job Performance (JP): (Vaziri et al., 2022)

JP1: I consistently achieve outcomes that meet or exceed performance requirements in my role; *JP2:* I ensure that all key tasks assigned to my position are fully completed; *JP3:* I make sure that the essential functions of my job are carried out effectively each day; *JP4:* I provide practical suggestions and support to improve how my team works with digital tools.

Table 1. Lower-Order Reliability and Convergent validity

Latent Variable	**Outer Loading**	**Cronbach's alpha**	**CR**	**AVE**
Inclusiveness (DEX)	0.841 - 0.890	0.821	0.893	0.736
Cohesiveness (DEX)	0.825 - 0.859	0.798	0.881	0.712
Technical Enablement (DEX)	0.838 - 0.861	0.802	0.883	0.716
Techno-overload	0.828 - 0.851	0.793	0.878	0.707
Techno-invasion	0.904 - 0.899	0.769	0.896	0.812
Techno-complexity	0.814 - 0.858	0.788	0.876	0.702
Techno-insecurity	0.825 - 0.857	0.799	0.882	0.713
Techno-uncertainty	1.000	1.000	1.000	1.000
Burnout	0.752 - 0.846	0.904	0.926	0.678
Turnover Intention	0.836 - 0.879	0.875	0.914	0.727
Job Performance	0.838 - 0.892	0.899	0.929	0.767

Table 2. Lower-Order Discriminant validity

HTMT	BO	Cohesiveness	Inclusiveness	JP	TC	TI	TIN	TINS	TO	TU	Technical Enablement
BO											
Cohesiveness	0.485										
Inclusiveness	0.498	0.797									
JP	0.613	0.407	0.404								
TC	0.566	0.468	0.493	0.430							
TI	0.768	0.334	0.333	0.356	0.412						
TIN	0.524	0.377	0.448	0.344	0.800	0.344					
TINS	0.471	0.436	0.459	0.391	0.774	0.331	0.678				
TO	0.559	0.471	0.502	0.415	0.779	0.343	0.663	0.653			
TU	0.527	0.361	0.424	0.414	0.731	0.412	0.629	0.732	0.612		
Technical Enablement	0.477	0.786	0.788	0.374	0.477	0.331	0.454	0.442	0.410	0.371	

Table 3. Higher-Order Reliability and Convergent Validity

Latent Variable	**Outer Loading**	**Cronbach's alpha**	**CR**	**AVE**
Digital Employee Experience	0.865 - 0.881	0.841	0.904	0.758
Technostress	0.785 - 0.863	0.875	0.909	0.667
Burnout	0.752 - 0.846	0.904	0.926	0.678
Turnover Intention	0.836 - 0.879	0.875	0.914	0.727
Job Performance	0.838 - 0.892	0.899	0.929	0.767

Table 4. Higher-Order Discriminant validity

HTMT	BO	DEX	JP	TI	TS
BO					
DEX	0.547				
JP	0.613	0.444			
TI	0.768	0.374	0.356		
TS	0.630	0.588	0.476	0.440	

Table 5. Hypothesis Test

Hyp.	***Relationships***	***β***	***t-values***	***p-values***	***f^2***	***R^2***	***95%CI (Bias-corrected)***	***Remarks***
H1	DEX → BO	-0.260	5.318	0.000	0.080	1.342	[-0.355; 0.164]	*Supported*
H2	DEX → TS	-0.505	12.273	0.000	0.342	1.000	[-0.580; 0.417]	*Supported*
H3	TS → BO	0.431	8.092	0.000	0.219	1.342	[0.320; 0.530]	*Supported*
H5	BO → TI	0.686	18.604	0.000	0.889	1.000	[0.607; 0.751]	*Supported*
H6	BO → JP	-0.553	15.267	0.000	0.440	1.342	[-0.618; 0.474]	*Supported*
	Indirect relationships							
H4	DEX→TS→BO	-0.218	7.020	0.000				*Supported*

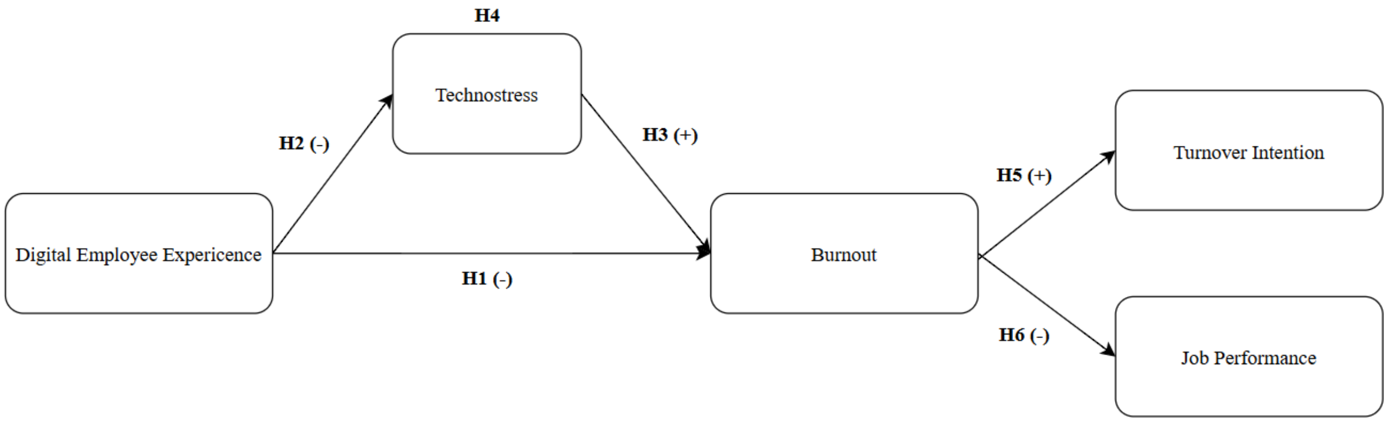

Fig.1 : Proposed research model

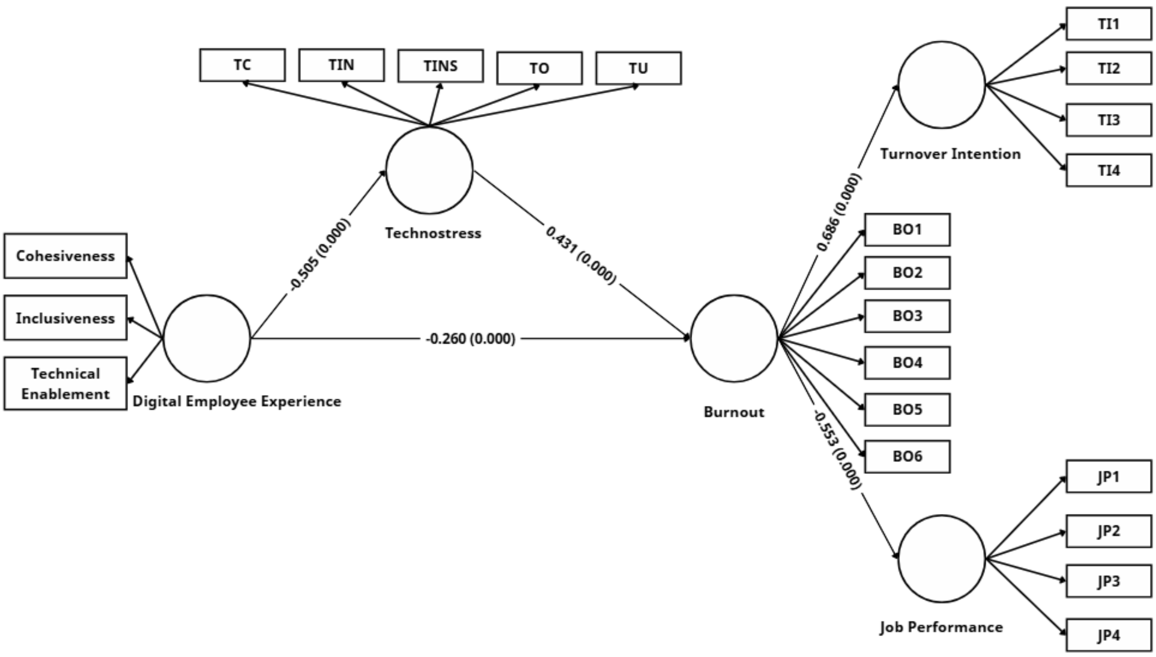

Fig.2: Results of the model based on bootstrapping