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Digital Upskilling, Cognitive Load, and Techno Fatigue: The Mediating Role of Work Autonomy

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ABSTRACT

Rapid digitalization in public institutions has intensified technology-related exhaustion among employees, yet the joint roles of digital competence, cognitive demands, and job control in shaping this exhaustion remain underexplored. Grounded in the Job Demands-Resources theory, this study examines the effects of digital upskilling and cognitive load on techno fatigue, with work autonomy as a mediating variable. A cross-sectional explanatory quantitative design was applied to technical employees of the Digital Technology Work Unit of Bank Indonesia. From a population of 284 employees, 150 respondents were selected through purposive sampling and completed an online 40-item five-point Likert questionnaire. The data were analyzed using partial least squares structural equation modeling in SmartPLS 4 with 5,000 bootstrap subsamples. All seven hypotheses were supported. Digital upskilling reduced techno fatigue and increased work autonomy, whereas cognitive load increased techno fatigue and reduced work autonomy. Work autonomy lowered techno fatigue and served as a complementary partial mediator in both paths, transmitting most of the effect of digital upskilling. Cognitive load showed the largest total effect and the lowest performance, making it the first priority for intervention. These findings indicate that digital training reduces fatigue most effectively when accompanied by the clear delegation of work discretion.

INTRODUCTION

Digital transformation has fundamentally changed the way organizations operate. Public institutions, including central banks, now depend on integrated digital systems to process data, supervise financial activities, and support policy decisions. Although this shift increases efficiency, the intensive use of technology also alters employees' behavior and psychological condition, creating new dynamics that organizations must understand comprehensively (Supriyadi et al., 2025). Employees are expected to adapt continuously to new systems and applications, yet not all of them have the same readiness to master technology and manage the accompanying workload. This uneven readiness increases the risk of work pressure and, ultimately, techno fatigue (Wang et al., 2023).

Techno fatigue refers to the physical and mental exhaustion that arises from the intensive use of digital technology at work. A systematic review by Bahamondes-Rosado et al. (2023) identified technology-related fatigue as one of the most frequently reported forms of technostress among workers. The condition is reflected in mental exhaustion, emotional exhaustion, techno-overload, and the blurring of boundaries between work and private life

(Supriyadi et al., 2025; Tarafdar et al., 2007). Maristya and Nurhayati (2024) further showed that technology-intensive work environments strongly affect employees' work–life balance, which makes the management of working-time boundaries essential for reducing technology-related exhaustion.

Three job characteristics are particularly relevant to techno fatigue. The first is employees' capacity to master technology. Digital upskilling, defined as the systematic development of employees' digital competence, can make employees more confident and technically proficient; however, programs that are poorly aligned with job requirements may hinder adaptation and increase pressure (Kashemsanta Na Ayudhya & Plangsorn, 2024; Van Laar et al., 2017). The second is cognitive load, namely the mental effort required to process information while performing a task. When employees must interact with several digital platforms simultaneously, the limited capacity of working memory is quickly exceeded (Chen et al., 2023; Skulmowski & Xu, 2022). Nastiti et al. (2025) demonstrated that information and communication overload received through digital channels triggers social media fatigue among Indonesian employees. The third is work autonomy, which determines the extent to which employees can regulate the timing, sequence, and methods of their work and thereby cope with technological demands (Baum & Rau, 2024; Hackman & Oldham, 1976).

These issues are salient in the Digital Technology Work Unit of Bank Indonesia, which plays a strategic role in realizing Bank Indonesia's vision of becoming a leading digital central bank. The unit develops software and digital innovations, manages data governance and advanced analytics, and maintains network infrastructure and cyber resilience. Its technical employees work with multiple systems at once under strict requirements for data accuracy, processing speed, and procedural compliance. A preliminary survey of 30 technical employees indicated that the available digital upskilling programs were perceived as ineffective, as employees still had to seek external training; cognitive load was at an alert level because of simultaneous interaction with several platforms; work autonomy was low, particularly in managing working time; and techno fatigue was high, as indicated by the blurred boundary between working and personal time. Preliminary interviews confirmed that work-related communication continued beyond formal working hours and that competing priorities forced employees to multitask.

A review of prior studies reveals four research gaps. First, research on digital competence and research on cognitive load have developed along separate streams; cognitive load has been studied mostly in educational psychology and has rarely been tested as a job demand in organizational settings (Chen et al., 2023; Skulmowski & Xu, 2022). Second, work autonomy has mostly been positioned as a direct predictor or a moderator (Msuya & Kumar, 2022). Zakariah et al. (2025) tested work autonomy as a mediator of fatigue, but the antecedent they examined was self-efficacy rather than a trainable digital competence that organizations can deliberately develop. Third, most studies examine general work exhaustion or burnout rather than fatigue that specifically originates from technology use (Hang et al., 2022; Wang et al., 2023). Fourth, empirical evidence on techno fatigue in state financial regulators, where work demands high accuracy and intensive system use, remains scarce. Accordingly, this study aims to analyze the effects of digital upskilling and cognitive load on techno fatigue, with work autonomy as a mediating variable, among technical employees of the Digital Technology Work Unit of Bank Indonesia. Theoretically, the study integrates competence, cognitive demand, and job control into a single Job Demands-Resources (JD-R) model; practically, it provides evidence-based priorities for managing technology-related fatigue in the public sector.

Literature Review and Hypothesis Development

The JD-R theory posits that every job has demands and resources that influence employees' well-being and performance. Job demands are aspects of work that require sustained physical, cognitive, or emotional effort and therefore carry psychological costs, whereas job resources help employees achieve work goals, reduce the costs of demands, and stimulate growth (Bakker & Demerouti, 2017; Demerouti et al., 2001). The theory distinguishes a health-impairment process, in which excessive demands deplete energy and lead to strain, from a motivational process, in which resources enhance capability and control. Resources also tend to generate other resources, forming gain spirals (Bakker & Demerouti, 2017). In this study, cognitive load is positioned as a job demand, digital upskilling as a personal resource, work autonomy as a job resource, and techno fatigue as a form of strain. Work autonomy was chosen as the mediator instead of digital efficacy for three reasons: it is a job resource operating at the level of work design, it is conceptually distinct from digital competence, and it can be directly adjusted by management through the delegation of authority.

Digital Upskilling and Techno Fatigue

The JD-R theory treats competence as a personal resource that enables individuals to meet job demands at a lower psychological cost (Bakker & Demerouti, 2017). Digital competence narrows the gap between system demands and user capabilities; Tarafdar et al. (2007) argued that complex new technologies become a burden precisely when such a gap exists. Hang et al. (2022) found that literacy facilitation acts as a technostress inhibitor among 355 banking employees, while Utari and Singagerda (2026) showed that digital literacy reduces technostress among civil servants through digital fluency. Berger et al. (2024) also identified competence development as one of the most widely agreed measures for preventing technostress.

H1: Digital upskilling has a negative and significant effect on techno fatigue.

Cognitive Load and Techno Fatigue

Cognitive load is a job demand that drains mental energy through the health-impairment process (Demerouti et al., 2001). Cognitive load theory explains that working memory has a limited capacity; therefore, tasks that require many interacting information elements to be processed simultaneously quickly exceed that capacity (Chen et al., 2023). Satpathy et al. (2021) identified technological complexity as a highly ranked stressor among information technology employees, and Wang et al. (2023) demonstrated that technostress reduces employee well-being through work exhaustion.

H2: Cognitive load has a positive and significant effect on techno fatigue.

Digital Upskilling and Work Autonomy

The Job Characteristics Model defines autonomy as the discretion to determine the methods, sequence, and timing of tasks (Hackman & Oldham, 1976). Such discretion can only be exercised when employees have the capacity to make informed choices. Mastery of problem-solving and information-management skills gives employees real options regarding the sequence and methods of work (Van Laar et al., 2017), reflecting the gain-spiral mechanism in which personal resources generate job resources (Bakker & Demerouti, 2017). Saraswaty and Pusparini (2023) found that competence and autonomy operate jointly among employees of an Indonesian public institution, and Zakariah et al. (2025) showed that personal resources significantly increase work autonomy.

H3: Digital upskilling has a positive and significant effect on work autonomy.

Cognitive Load and Work Autonomy

Cognitive capacity is limited and cannot be allocated twice (Skulmowski & Xu, 2022). Cognitive resources consumed by understanding systems and processing information are no longer available for comparing alternatives, setting priorities, and making independent

decisions. Consequently, high cognitive demands erode the discretion that employees formally possess. Satpathy et al. (2021) reported that technological complexity increases reliance on centralized technical support, which implies reduced independence, while Msuya and Kumar (2022) found that workload is negatively associated with outcomes among banking employees.

H4: Cognitive load has a negative and significant effect on work autonomy.

Work Autonomy and Techno Fatigue

Work autonomy is a job resource that reduces the psychological costs of job demands (Bakker & Demerouti, 2017). The discretion to arrange time, methods, sequence, and priorities allows employees to align digital demands with their capacity and work rhythm, thereby limiting the accumulation of fatigue. Baum and Rau (2024) found that autonomy strengthens work–life balance, Anual et al. (2023) reported a positive relationship between autonomy and job satisfaction in the telecommunication industry, and Zakariah et al. (2025) demonstrated that work autonomy significantly reduces fatigue.

H5: Work autonomy has a negative and significant effect on techno fatigue.

The Mediating Role of Work Autonomy

If digital upskilling increases work autonomy (H3) and work autonomy reduces techno fatigue (H5), an indirect path from digital upskilling to techno fatigue through work autonomy is expected. This chain represents a gain spiral in which one resource generates another before producing the desired outcome. Berger et al. (2024) emphasized that competence development and the provision of job control are complementary preventive measures that should be implemented together. Similarly, if cognitive load reduces work autonomy (H4), cognitive load should increase techno fatigue indirectly by eroding the resource that is supposed to protect employees. Anggraini and Wulandari (2026) found that technostress affects the performance of Indonesian digital workers through digital fatigue, supporting the existence of such layered mechanisms.

H6: Work autonomy mediates the negative effect of digital upskilling on techno fatigue.

H7: Work autonomy mediates the positive effect of cognitive load on techno fatigue.

The research framework, which summarizes the seven hypotheses, is presented in Figure 1.

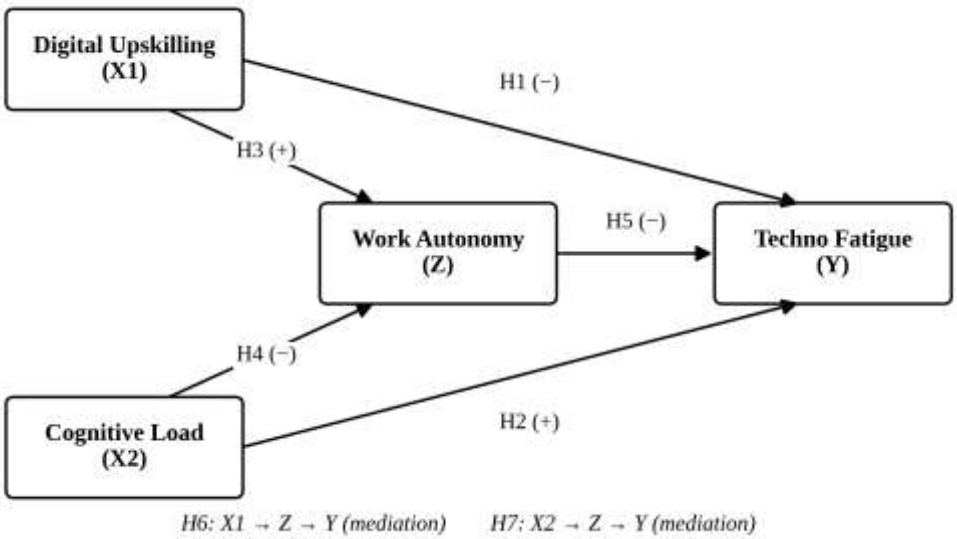


Figure 1. Research Framework

METHOD

This study employed an explanatory quantitative approach with a cross-sectional survey design to test the causal relationships among digital upskilling (X1), cognitive load (X2), work

autonomy (Z), and techno fatigue (Y). The population comprised all 284 technical employees of the Digital Technology Work Unit of Bank Indonesia, who use digital systems and applications as their primary work tools. Purposive sampling was applied using four inclusion criteria: (1) holding a technical position in the unit; (2) using digital systems or applications as the main means of performing daily tasks; (3) having attended at least one internal or external digital competence development activity; and (4) being willing to participate and complete all questionnaire items. The sample size of 150 respondents, equivalent to 52.82% of the population, exceeds the minimum of ten times the number of variables recommended by Sekaran and Bougie (2016) and falls within the range of five to ten times the number of indicators (100–200 respondents) suggested for structural equation modeling (Ferdinand, 2014). The questionnaire was distributed online through Google Forms, and 150 complete responses were obtained.

The instrument consisted of 40 closed-ended statements measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The four constructs comprised 11 dimensions and 20 indicators; each construct was operationalized through five indicators, and each indicator was measured by two items, resulting in ten items per construct. All constructs were modeled as first-order reflective constructs. The dimensions and item sources are summarized in Table 1. In addition, preliminary semi-structured interviews and internal documents were used to contextualize the phenomenon, but they were not used for hypothesis testing.

Table 1. Construct Operationalization

Construct	Dimensions	Sample Item	Source
Digital Upskilling (X1; 10 items)	Digital competence (indicators: application use; digital information management; digital communication and collaboration; technology-based problem solving; self-learning and adaptation)	"I can resolve technical problems in the application I am using without always relying on the helpdesk."	Van Laar et al. (2017)
Cognitive Load (X2; 10 items)	Intrinsic load; extraneous load (information overload and non-intuitive system design); germane load (processing, integrating, and evaluating information)	"I need extra concentration to remember the operating steps of new features in work applications."	Chen et al. (2023); Skulmowski & Xu (2022)
Work Autonomy (Z; 10 items)	Scheduling autonomy; work-method autonomy; decision-making autonomy	"I am free to choose the method that I consider most effective for completing my work."	Hackman & Oldham (1976)
Techno Fatigue (Y; 10 items)	Mental exhaustion; emotional exhaustion; techno-overload; work–life boundary blur	"I feel tired because technology requires me to complete work much faster."	Bahamondes-Rosado et al. (2023); Supriyadi et al. (2025); Tarafdar et al. (2007)

Source: Compiled by the authors (2026)

The data were analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4. PLS-SEM was selected because it allows the measurement model, the structural model, and the direct and indirect effects through work autonomy to be analyzed simultaneously, and it does not require interval-scaled data or a normal distribution (Hair et al., 2022). The analysis proceeded in several stages. First, descriptive statistics were computed,

and item means were interpreted using five equal class intervals (1.00–1.80 very low; 1.81–2.60 low; 2.61–3.40 moderate; 3.41–4.20 high; 4.21–5.00 very high). Second, the measurement model was evaluated using outer loadings (> 0.70), average variance extracted (AVE > 0.50), Cronbach's alpha, rho_A, and composite reliability (> 0.70), the heterotrait–monotrait ratio (HTMT < 0.90), the Fornell–Larcker criterion, and outer variance inflation factors (VIF < 5.00) (Hair et al., 2019, 2022).

Third, the structural model was evaluated using inner VIF, the coefficient of determination (R^2), effect size (f^2), and the standardized root mean square residual (SRMR < 0.08). Predictive relevance was assessed using PLSpredict with ten folds and ten repetitions, because this procedure evaluates out-of-sample prediction rather than the in-sample relevance assessed by blindfolding (Sarstedt et al., 2023; Shmueli et al., 2019); it was complemented by the cross-validated predictive ability test (CVPAT) at the model level (Liengaard et al., 2021; Sharma et al., 2023). An importance–performance map analysis (IPMA) with techno fatigue as the target construct was performed to identify managerial priorities. Because techno fatigue is an undesirable outcome, importance was interpreted from the absolute value of the total effect, while its sign indicated the direction of influence. Finally, the hypotheses were tested using bootstrapping with 5,000 subsamples; a relationship was considered significant when the t-statistic exceeded 1.96 and the p-value was below 0.05 (two-tailed). Mediation was classified by comparing the significance and direction of the direct and indirect effects (Hair et al., 2022).

RESULTS AND DISCUSSION

Respondent Profile and Descriptive Statistics

Of the 150 respondents, 83 (55.33%) were female and 67 (44.67%) were male. Most respondents were aged 31–40 years (83; 55.33%), followed by those aged 41–50 years (42; 28.00%), 25–30 years (16; 10.67%), and above 50 years (9; 6.00%). Among those who reported their tenure in the unit, the largest groups had served for 5–10 years (40; 26.67%) and 11–15 years (36; 24.00%), whereas 38 respondents (25.33%) did not report their tenure. Because only nine respondents were older than 50 years, the findings should be generalized to senior employees with caution, particularly since Porcari et al. (2023) observed the highest technostress levels among older banking employees. Evidence on gender differences in technostress is also inconsistent (Marchiori et al., 2019; Porcari et al., 2023); therefore, the demographic variables were used only for descriptive purposes.

Table 2 presents the descriptive statistics of the research variables. Digital upskilling was in the high category, with the weakest item being the ability to resolve technical problems without relying on the helpdesk (X1.08; mean = 3.687). Cognitive load was moderate; the strongest sources of load were the need to evaluate information before using it (X2.10; 3.813) and the requirement to understand digital systems in great detail (X2.01; 3.587), whereas difficulties caused by interface design were the lowest (X2.05; 2.727 and X2.06; 2.713). Work autonomy was high, but the ability to make decisions under urgent conditions was its weakest aspect (Z1.07; 3.533). Techno fatigue was moderate, with the highest scores on the pressure to multitask (Y1.06; 3.593) and the blurring of rest and working time caused by work chat groups (Y1.09; 3.540), and the lowest score on irritation with technology dependence (Y1.04; 2.500).

Table 2. Descriptive Statistics of Research Variables

Variable	Mean	Lowest Item (Mean)	Highest Item (Mean)	Category
Digital Upskilling (X1)	4.085	X1.08 (3.687)	X1.06 (4.280)	High
Cognitive Load (X2)	3.133	X2.06 (2.713)	X2.10 (3.813)	Moderate
Work Autonomy (Z)	3.663	Z1.07 (3.533)	Z1.10 (3.780)	High
Techno Fatigue (Y)	3.039	Y1.04 (2.500)	Y1.06 (3.593)	Moderate

Source: Primary data processed (2026)

The moderate level of techno fatigue differs from the high level suggested by the preliminary survey. This difference can be explained in three ways. First, the preliminary survey involved 30 employees and one statement per variable and served to explore the phenomenon rather than to measure its level, whereas the main study used ten items per construct across 150 respondents. Second, the preliminary item focused on the blurred boundary between working and personal time, and this aspect was confirmed in the main study as one of the highest-scoring indicators. Third, the moderate category does not negate the urgency of the problem; rather, it shows that techno fatigue in this unit is concentrated in specific dimensions, namely multitasking demands and boundary blur, which sharpens the focus of organizational interventions.

Measurement Model Evaluation

All 40 indicators had outer loadings above 0.70, ranging from 0.749 to 0.836; hence, no indicator was removed. As shown in Table 3, Cronbach's alpha, rho_A, and composite reliability exceeded 0.90 for all constructs, and all AVE values exceeded 0.50, confirming internal consistency reliability and convergent validity. Outer VIF values ranged from 2.042 to 3.736, indicating the absence of problematic collinearity among indicators.

Table 3. Reliability and Convergent Validity

Construct	Loading Range	Cronbach's α	rho_A	CR	AVE	Outer VIF Range
Digital Upskilling	0.751–0.815	0.932	0.934	0.942	0.620	2.205–2.674
Cognitive Load	0.749–0.822	0.929	0.934	0.940	0.611	2.107–3.736
Work Autonomy	0.783–0.808	0.937	0.938	0.946	0.638	2.326–2.817
Techno Fatigue	0.759–0.836	0.931	0.933	0.942	0.618	2.042–3.348

Source: SmartPLS 4 output (2026)

Discriminant validity was established by both criteria (Table 4). All HTMT values were below 0.90, with the highest value observed between work autonomy and techno fatigue (0.745). The square root of the AVE of each construct was greater than its correlations with the other constructs, satisfying the Fornell–Larcker criterion.

Table 4. Discriminant Validity: Fornell–Larcker Criterion and HTMT

Construct	X1	X2	Z	Y
Digital Upskilling (X1)	**0.788**	0.481	0.663	0.650
Cognitive Load (X2)	−0.454	**0.782**	0.467	0.674
Work Autonomy (Z)	0.626	−0.447	**0.799**	0.745
Techno Fatigue (Y)	−0.615	0.643	−0.703	**0.786**

Note: Diagonal values (bold) are the square roots of AVE; values below the diagonal are construct correlations; values above the diagonal are HTMT ratios. Source: SmartPLS 4 output (2026)

Structural Model Evaluation

Inner VIF values ranged from 1.260 to 1.754, indicating no collinearity among the predictor constructs. As presented in Table 5, digital upskilling, cognitive load, and work autonomy jointly explained 64.8% of the variance in techno fatigue ($R^2 = 0.648$), which is moderate and approaching substantial, whereas digital upskilling and cognitive load explained 42.5% of the variance in work autonomy ($R^2 = 0.425$), which is moderate (Hair et al., 2019). Both $Q^2_{predict}$ values were greater than zero, confirming the predictive relevance of the model. The SRMR value of 0.072 was below 0.08, indicating an adequate model fit.

Table 5. Coefficient of Determination and Predictive Relevance

Endogenous Construct	R^2	Adjusted R^2	$Q^2_{predict}$	Interpretation
Techno Fatigue (Y)	0.648	0.641	0.527	Moderate; predictive relevance
Work Autonomy (Z)	0.425	0.417	0.400	Moderate; predictive relevance

Source: SmartPLS 4 output (2026)

At the indicator level, PLSpredict showed that all ten work autonomy indicators produced lower root mean squared error (RMSE) values than the linear model benchmark, indicating high predictive power for this construct, while five of the ten techno fatigue indicators did so, indicating medium predictive power (Shmueli et al., 2019). At the model level, CVPAT confirmed that the PLS-SEM model had significantly lower prediction losses than both the indicator-average benchmark (average loss difference = −0.322; $p < 0.001$) and the linear model benchmark (average loss difference = −0.056; $p = 0.040$). Therefore, the model has adequate overall predictive ability.

Hypothesis Testing

Figure 2 and Table 6 present the results of the bootstrapping procedure. All five direct effects were significant in the hypothesized directions. Digital upskilling had a negative effect on techno fatigue ($\beta = -0.181$; $p = 0.015$) and a positive effect on work autonomy ($\beta = 0.533$; $p < 0.001$); the latter was the strongest relationship in the model and the only one with a large effect size ($f^2 = 0.392$). Cognitive load had a positive effect on techno fatigue ($\beta = 0.371$; $p < 0.001$) and a negative effect on work autonomy ($\beta = -0.205$; $p = 0.005$). Work autonomy had the largest direct effect on techno fatigue ($\beta = -0.424$; $p < 0.001$). Thus, H1–H5 were supported.

Table 6. Results of Hypothesis Testing

Hypothesis	Path	β	t-statistic	p-value	f^2	Decision
H1	X1 → Y	−0.181	2.444	0.015	0.053	Supported
H2	X2 → Y	0.371	6.534	< 0.001	0.294	Supported
H3	X1 → Z	0.533	7.148	< 0.001	0.392	Supported
H4	X2 → Z	−0.205	2.797	0.005	0.058	Supported
H5	Z → Y	−0.424	6.024	< 0.001	0.295	Supported
H6	X1 → Z → Y	−0.226	4.662	< 0.001	–	Supported
H7	X2 → Z → Y	0.087	2.579	0.010	–	Supported

Note: X1 = digital upskilling; X2 = cognitive load; Z = work autonomy; Y = techno fatigue; H6 and H7 represent complementary partial mediation. Source: SmartPLS 4 output (2026)

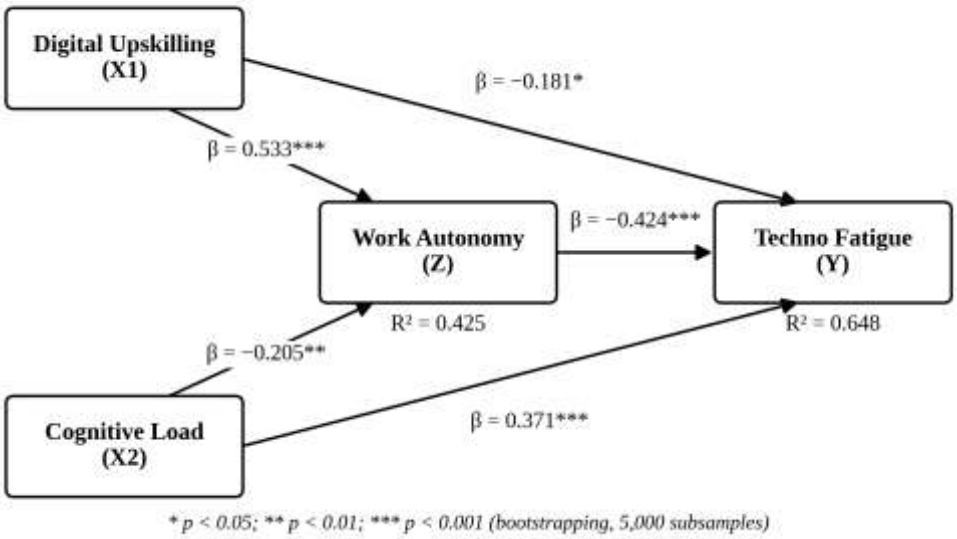


Figure 2. Structural Model Results

The indirect effect of digital upskilling on techno fatigue through work autonomy was significant (β = −0.226; p < 0.001). Because the direct effect remained significant and had the same sign, work autonomy acted as a complementary partial mediator, and H6 was supported. The indirect effect was larger than the direct effect, and the total effect of digital upskilling on techno fatigue was −0.407. The indirect effect of cognitive load on techno fatigue through work autonomy was also significant (β = 0.087; p = 0.010), again indicating complementary partial mediation; thus, H7 was supported. In contrast to the first path, the direct effect was considerably larger than the indirect effect, and the total effect of cognitive load on techno fatigue was 0.458. The structural equations are Z = 0.533X1 − 0.205X2 and Y = −0.181X1 + 0.371X2 − 0.424Z.

Importance–Performance Map Analysis

Table 7. Importance–Performance Map Analysis (Target: Techno Fatigue)

Construct	Importance (Total Effect)	Performance (0–100)	Priority
Cognitive Load	0.458	52.67	First
Work Autonomy	−0.424	66.57	Second
Digital Upskilling	−0.407	76.91	Third (maintain)

Source: SmartPLS 4 output (2026)

As shown in Table 7, cognitive load had the highest importance for techno fatigue and the lowest performance, placing it in the top-priority quadrant. The negative importance values of work autonomy and digital upskilling do not indicate low importance; they indicate that improving these constructs reduces an undesirable outcome. Work autonomy had an importance nearly equal to that of cognitive load but a medium level of performance, leaving considerable room for improvement. Digital upskilling had the highest performance; therefore, its role is to be maintained and redirected rather than repaired.

Discussion

The Effect of Digital Upskilling on Techno Fatigue

The negative effect of digital upskilling on techno fatigue supports the JD-R view of competence as a personal resource that buffers the depletion of energy (Bakker & Demerouti, 2017; Demerouti et al., 2001). When employees master the systems they use, they complete tasks with fewer steps and fewer errors, so their psychological energy is not depleted as quickly. This mechanism is consistent with Tarafdar et al. (2007), who argued that technological complexity becomes a burden when there is a gap between system demands and user capabilities, and with Hang et al. (2022), who found that digital literacy facilitation weakens the negative effects of technostress on banking employees. Nevertheless, this direct effect was the weakest in the model. Following Berger et al. (2024), digital training can be regarded as a primary preventive measure that acts before strain emerges; therefore, its direct footprint on fatigue is smaller than that of factors operating once fatigue has developed. The descriptive pattern further shows that employees are strong in application use and digital communication but weaker in independent troubleshooting, the skill domain that confronts the sources of fatigue most directly (Van Laar et al., 2017). Future training programs should therefore emphasize diagnosis and problem solving rather than introducing features that employees have already mastered.

The Effect of Cognitive Load on Techno Fatigue

Cognitive load was the demand with the strongest influence on techno fatigue, which represents the clearest manifestation of the health-impairment process in the JD-R theory (Demerouti et al., 2001). Cognitive load theory explains this finding at a finer level: because working memory is limited, work that requires employees to operate several applications simultaneously while maintaining data accuracy quickly exceeds its capacity (Chen et al., 2023). Importantly, not all cognitive load is alike. Skulmowski and Xu (2022) distinguished load arising from information presentation, which can be removed without reducing the substance of work, from load inherent in task complexity. In this study, the pressure stemmed mainly from the need to understand systems in depth and to verify information before use, whereas interface-related difficulties were the lowest. In an institution with financial supervisory functions, careful verification is expected behavior; hence, the resulting load

should be managed rather than eliminated. This finding is consistent with Wang et al. (2023), Anggraini and Wulandari (2026), and Hashona and Pusparini (2026), who found that technostress increases exhaustion among auditors of a state financial supervisory institution.

The Effect of Digital Upskilling on Work Autonomy

The effect of digital competence on work autonomy was the strongest relationship in the model. This result shows that autonomy is not merely granted by organizational policy; employees must also be able to use it. Employees who have not mastered their systems face layered constraints: they recognize fewer alternative methods, they hesitate to bear the consequences of technical decisions and tend to escalate problems, and their attention is consumed by understanding the system rather than by strategic considerations. Conversely, problem-solving and information-management skills give employees real choices regarding the sequence, methods, and priorities of their work (Van Laar et al., 2017). This pattern empirically illustrates the gain spiral proposed by Bakker and Demerouti (2017) and is consistent with Saraswaty and Pusparini (2023). For the institution, the implication is direct: the delegation of authority will be effective only if it is preceded, or at least accompanied, by the strengthening of digital competence.

The Effect of Cognitive Load on Work Autonomy

Cognitive load reduced perceived work autonomy, albeit with a small effect size. This finding should be interpreted carefully because the construct measured here is not formal authority as stated in job descriptions but the discretion that employees can actually exercise in daily work. Cognitive resources absorbed by understanding systems and remembering operating steps are no longer available for comparing alternatives and setting priorities (Chen et al., 2023). In addition, systems that require considerable effort merely to navigate push employees to follow predefined system flows, because searching for alternative routes adds further load (Skulmowski & Xu, 2022). In other words, discretion narrows not because it is prohibited, but because it becomes too cognitively costly to use. This result is in line with Satpathy et al. (2021), who reported that technological complexity increases dependence on centralized technical support. Notably, decision-making under urgent conditions was the weakest aspect of autonomy, and independent troubleshooting was the weakest aspect of digital competence; both point to the same remedy, namely simplifying cognitive demands while clarifying decision rights.

The Effect of Work Autonomy on Techno Fatigue

Work autonomy exerted the largest direct effect in reducing techno fatigue, supporting the Job Characteristics Model (Hackman & Oldham, 1976) and the JD-R view of autonomy as a job resource that reduces the psychological costs of demands (Bakker & Demerouti, 2017). The most prominent forms of fatigue in this study, namely multitasking pressure and blurred boundaries between work and rest, concern the rhythm and connectivity of work rather than the rejection of technology, and this rhythm is precisely what autonomy controls. Baum and Rau (2024) likewise found that job autonomy determines whether flexibility actually reduces negative spillover from work to private life. However, autonomy is not unconditional. Wan et al. (2024) showed that autonomy can increase positive emotions but may also increase work alienation when expectations are unclear, and Msuya and Kumar (2022) showed that autonomy works best when it is supported by supervisors. For an institution with strict procedures and high accountability, autonomy should therefore take the form of explicit decision boundaries and clear escalation mechanisms, accompanied by rules on after-hours communication so that flexibility does not turn into a demand for constant availability (Wells et al., 2023).

The Mediating Role of Work Autonomy

The mediating role of work autonomy in the digital upskilling path constitutes the main theoretical contribution of this study. The benefits of digital competence in reducing techno fatigue do not end with technical mastery; they operate mainly through employees' increased control over their own work, as the indirect path contributed more than the direct path. This pattern reflects the motivational process of the JD-R theory, in which personal resources generate job resources that subsequently buffer strain, and it provides empirical evidence for a specific form of gain spiral in digital work: from digital competence to work discretion and, finally, to reduced techno fatigue (Bakker & Demerouti, 2017). Such a sequential chain has rarely been tested explicitly in technostress research, which has predominantly examined direct relationships between competence and fatigue.

By contrast, in the cognitive load path, most of the effect operated directly, and only a small portion flowed through work autonomy. This asymmetry can be explained by the nature of the two variables. Cognitive load attacks mental capacity immediately, because overloaded working memory produces fatigue without an intermediary (Chen et al., 2023), whereas the erosion of discretion is a slower process, especially in organizations with established authority structures. The managerial implication is clear: to maximize the benefits of digital upskilling, organizations must strengthen autonomy, whereas to address cognitive load, system simplification and the reduction of information-processing demands remain the principal interventions, with autonomy serving as additional protection against the digital demands that cannot be eliminated.

Theoretical and Practical Implications

Theoretically, this study extends the JD-R theory by integrating digital competence, cognitive demand, and job control into a single model of technology-specific fatigue in a public-sector setting. It shows that work autonomy functions not only as an independent job characteristic, as described in the Job Characteristics Model, but also as an intervening mechanism that translates technological mastery into lower technology-related strain. The findings also support the relevance of Sustainable Development Goals 3 and 8, as the protection of employees' mental health and the provision of decent, autonomous work are both required for sustainable digital transformation.

Practically, the IPMA results and the strongest-loading items suggest the following order of intervention. First, cognitive load should be reduced by scheduling feature releases through a shared calendar between system owners and user units, providing task-based guides and short onboarding support for new features, applying progressive disclosure in interfaces, and reducing the number of applications required to complete one work process. Second, work autonomy should be strengthened by allowing employees to set the sequence and rhythm of tasks as long as deadlines are met, clarifying decision rights and escalation procedures for urgent situations, and protecting procedurally compliant technical initiatives. Third, digital upskilling should be maintained and redirected toward troubleshooting skills through structured learning paths. In addition, the organization should classify task urgency, set response-time standards for digital communication, and separate official reporting channels from informal chat groups. These measures should be designed as one integrated annual program rather than as separate initiatives.

CONCLUSION

This study concludes that all research objectives were achieved and all hypotheses were supported, as follows: Digital upskilling reduces techno fatigue: the better employees can use,

understand, and solve problems with technology, the lower the technology-related fatigue they experience. Cognitive load increases techno fatigue and is the main risk factor in the model, as reflected in its largest total effect and lowest performance. Digital upskilling increases work autonomy and represents the strongest relationship in the model. Cognitive load reduces work autonomy by limiting employees' mental capacity to make decisions and control their work independently. Work autonomy reduces techno fatigue and has the largest direct effect among all tested paths. Work autonomy complementarily and partially mediates the effect of digital upskilling on techno fatigue, and the indirect path is larger than the direct path. Work autonomy complementarily and partially mediates the effect of cognitive load on techno fatigue, although most of this effect operates directly.

Therefore, techno fatigue should be managed through an integrated strategy that reduces unnecessary cognitive load, strengthens work autonomy within clear boundaries of authority, and enhances digital upskilling. This study has several limitations. The cross-sectional design limits causal inference; all data were self-reported by the same respondents; the study was conducted in a single work unit; 38 respondents did not report their tenure; digital upskilling was measured as perceived competence rather than training intensity or quality; and IPMA performance values reflect perceptions rather than objective indicators. Future studies are encouraged to use longitudinal or pre–post designs around digital training programs, extend the research to multiple institutions and sectors with multigroup analyses by age, tenure, and task type, include additional variables such as digital efficacy, organizational support, digital organizational culture, and leadership, and combine perceptual data with objective measures such as the number of applications used, screen time, notification frequency, and system disruptions.

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The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

Aliya Savitri: conceptualization, methodology, data collection, formal analysis, and writing of the original draft. Nia Kusuma Wardhani: supervision, validation, and review and editing of the manuscript.

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The author(s) declared that generative AI was used in the creation of this manuscript. The author(s) wish to acknowledge the use of generative AI for refining the language clarity and grammatical structure of this manuscript. This application was conducted in adherence to established ethical guidelines regarding the use and disclosure of generative AI in scholarly research. Each author has provided substantial intellectual contributions to the work, which has been rigorously vetted for accuracy, and the author(s) assume full responsibility for the integrity and final content of the manuscript.

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