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Efficiency Overload: A Dual-Mechanism Analysis of AI Adoption and Employee Wellbeing in Islamic Microfinance Institutions

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Abstract

The adoption of artificial intelligence (AI) in Baitul Maal wat Tamwil (BMT) institutions is expected to improve work efficiency, yet its impact on employees' psychological wellbeing remains inconclusive. This study examines the effect of AI adoption on employee wellbeing through three mediating mechanisms by integrating the Job Demands-Resources (JD-R) and Conservation of Resources (COR) theories. Data were collected from 338 BMT employees in Purwokerto and Purbalingga using purposive sampling and analyzed with Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS. The results indicate that AI adoption significantly increases task optimization, workplace safety, and techno-overload, but has no direct effect on employee wellbeing. Contrary to the hypotheses, task optimization negatively affected wellbeing by reducing human interaction and the perceived meaningfulness of work, whereas techno-overload positively influenced wellbeing because employees perceived it as eustress that encouraged competence development. Workplace safety showed no significant effect, as it was regarded as a basic organizational standard rather than a source of additional wellbeing. These findings suggest that AI influences employee wellbeing indirectly through employees' psychological interpretations of technological change. The study extends JD-R and COR theories and highlights the importance of balancing digital efficiency with human interaction and psychosocial support during digital transformation.

Keywords: AI Adoption, Employee Well-being, Workplace Safety, Techno-Overload, Task Optimization, Islamic Microfinance Institutions (BMT).

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INTRODUCTION

AI-driven digital transformation has changed the way organizations work, interact, and make decisions. AI adoption now extends to the financial sector, including Islamic microfinance institutions such as Baitul Maal wat Tamwil (BMT). Globally, AI has been shown to improve operational efficiency, speed up decision-making, and optimize employee performance through automation and analytics support (Dwivedi et al., 2023; Hillebrand et al., 2025). However, the use of AI also creates new pressures in the form of technological complexity, digital workload, and high demands for adaptation (Bankins et al., 2024; Tarafdar et al., 2023), so that AI is not merely a technological issue but also a psychological and organizational one.

In BMT, digitalization is becoming a strategic necessity to improve competitiveness. The use of AI in financing, risk analysis, and customer service is expanding. However, BMT's characteristics, which are grounded in trust, social closeness, and Islamic values, mean that technology adoption does not always proceed smoothly. Challenges such as limited human resources, technological readiness, and adaptation pressure still frequently arise (Hasan, R., & Ali, 2023; Liu et al., 2024). In particular, human-resource competency in BMT remains a fundamental issue in the AI-adoption process: most BMT employees do not yet possess adequate digital literacy and technical skills to operate AI-based systems optimally, while available training remains limited and has not reached all levels of staff (Hasan, R., & Ali, 2023; Jaiswal et al., 2023). This competency gap has the potential to widen the adaptation pressure employees experience, while also preventing the organization from fully capturing the benefits of its technology investment (Liu et al., 2024). This raises the question of how AI affects employee wellbeing in organizations that are not fully technology-based and that still face human-resource competency constraints.

Prior research shows inconsistent results regarding the effect of AI on employee wellbeing. Some studies find a positive impact through improved work efficiency (Chuang et al., 2025; Valtonen et al., 2025), while others show increased stress, digital fatigue, and psychological pressure (Giuntella et al., 2025; Jaya et al., 2026). There are even non-significant findings due to intervening factors (Routray et al., 2025). This indicates that the relationship between AI and wellbeing is not direct, but operates through certain mechanisms.

This study adopts the Job Demands-Resources (JD-R) approach, which explains that working conditions consist of resources that enhance wellbeing and job demands that have the potential to diminish it (Demerouti & Bakker, 2023). AI adoption can function as a resource through efficiency and job security, but also as a demand through technological pressure. This explanation is reinforced by Conservation of Resources (COR) theory, which emphasizes that

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resource loss triggers stress and declining wellbeing (Hobfoll et al., 2023). Integrating these two approaches helps explain the variation in AI's impact on wellbeing.

Inconsistency is also apparent in the relationships among variables. The effect of AI adoption on task optimization tends to be positive but not always significant, owing to skill gaps and resistance (Jaiswal et al., 2023; Parker & Grote, 2023; Valtonen et al., 2025). The relationship with workplace safety also varies between increased security and emerging feelings of insecurity due to surveillance and job uncertainty (Bankins et al., 2024; Falco et al., 2023). For techno-overload, some studies show increased workload, while others find effects that can be minimized or are non-significant (Jaya et al., 2026; Routray et al., 2025; Tarafdar et al., 2023). The direct relationship between AI adoption and employee wellbeing is likewise inconsistent, being positive, negative, or non-significant across studies (Giuntella et al., 2025; Routray et al., 2025; Valtonen et al., 2025). A similar pattern occurs in the relationship between the mediators and wellbeing, where task optimization and workplace safety are generally positive but not always significant, while techno-overload tends to be negative but context-dependent (Falco et al., 2023; Parker & Grote, 2023; Tarafdar et al., 2023).

The research gap identified from the discussion above is that prior studies tend to examine the positive and negative effects of AI separately and partially (Routray et al., 2025; Valtonen et al., 2025), so that few have simultaneously tested a positive pathway (through *task optimization*) and a negative pathway (through *techno-overload*) within one integrated dual-mechanism model particularly in the context of Islamic microfinance institutions such as BMT, which have distinctive socio-religious characteristics and limited human-resource competency in adopting new technology (Asmini, 2025; Hasan, R., & Ali, 2023).

To address this gap, this study aims to analyze the effect of *AI adoption* on *employee well-being* through three simultaneous mediating pathways, namely *task optimization*, *workplace safety*, and *techno-overload*, in the context of BMT in Indonesia (Asmini, 2025). This study offers a *dual-mechanism* model that combines a positive pathway through *task optimization* and a negative pathway through *techno-overload* in explaining AI's effect on employee wellbeing. Its contribution lies in developing a model that explains AI's effects simultaneously while presenting the context of Islamic microfinance institutions, which remains limited in the literature thereby extending the scope of AI research in Islamic microfinance institutions while highlighting human-asset management during digital transformation.

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LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Theoretical Foundation

This study uses two main approaches to explain the relationship between AI adoption and employee wellbeing: Job Demands-Resources (JD-R) and Conservation of Resources (COR). Job Demands-Resources theory explains that working conditions consist of resources that can enhance motivation and job demands that have the potential to cause fatigue and stress (Demerouti & Bakker, 2023). In this regard, technology such as AI can function as a resource when it improves work efficiency and security, but can also become a job demand when it adds complexity and digital workload. This is reinforced by Conservation of Resources theory, which states that individuals tend to protect and build up the resources they possess, while resource loss triggers psychological strain (Hobfoll et al., 2023). When AI helps simplify work, employees gain additional energy and capacity; conversely, when AI increases cognitive load and adaptation demands, individual resources become depleted. These two approaches complement each other in explaining why the same technology can produce different effects on employee wellbeing.

HYPOTHESIS DEVELOPMENT

Artificial Intelligence Adoption on Task Optimization

Artificial intelligence adoption refers to the extent to which AI-based technology is used and integrated into day-to-day work activities to support decision-making and task completion (Dwivedi et al., 2023). Meanwhile, *task optimization* describes the extent to which work can be completed more efficiently, quickly, and accurately with technological support (Robbins & Judge, 2017). JD-R explains that technology can function as a job resource that enhances efficiency and performance. When AI is used to automate routine tasks and provide more accurate analysis, employees can allocate energy toward more strategic work. COR further asserts that improved work efficiency reflects an accumulation of resources that positively affects individuals. A number of studies show that AI adoption contributes to improved efficiency and task optimization (Chuang et al., 2025; Hannigan, 2024; Valtonen et al., 2025). AI technology helps reduce repetitive work and improve output quality. Thus, the relationship between AI adoption and task optimization tends to be positive. Considering this argument, the following hypothesis is proposed:

H1: Artificial intelligence adoption has a positive effect on task optimization.

ARTIFICIAL INTELLIGENCE ADOPTION ON WORKPLACE SAFETY

Artificial intelligence adoption is also related to an organization's ability to improve

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workplace safety through technology-based systems. *Workplace safety* reflects working conditions that are physically and psychologically safe, including protection from work errors and operational risk (Ciccarelli, 2024). AI technology can improve safety through monitoring systems, risk detection, and reduced human error. JD-R explains that safe working conditions constitute a resource that supports wellbeing. COR further asserts that a sense of security enhances psychological stability and preserves individual resources. Research shows that AI use can improve workplace safety and reduce error risk (Chuang et al., 2025; Ciccarelli, 2024; Falco et al., 2023). AI-based systems help employees work in a more controlled and structured manner. Therefore, the relationship between AI adoption and workplace safety tends to be positive. Based on this discussion, the following hypothesis can be formulated:

H2: Artificial intelligence adoption has a positive effect on workplace safety.

Artificial Intelligence Adoption on Techno-Overload

Artificial intelligence adoption can also increase work pressure through increasingly complex technological demands. *Techno-overload* describes a condition in which employees feel burdened by the use of technology that demands speed, multitasking, and a high degree of adaptation (Tarafdar et al., 2023). JD-R explains that high job demands can drain energy and cause stress. COR asserts that pressure arising from technology reflects a loss of individual resources. When AI increases workload volume and task complexity, employees are at risk of experiencing overload. Research shows that digital-technology adoption increases workload and psychological pressure (Jaya et al., 2026; Ragu-Nathan, 2023; Tarafdar et al., 2023). The use of AI is often followed by higher performance demands and an accelerated pace of work. Therefore, the relationship between AI and techno-overload tends to be positive. In line with this explanation, the following hypothesis is proposed:

H3: Artificial intelligence adoption has a positive effect on techno-overload.

Artificial Intelligence Adoption on Employee Wellbeing

Employee wellbeing refers to employees' psychological and emotional condition, reflecting the balance between job demands and individual satisfaction (Diener et al., 2018). AI adoption can affect wellbeing directly through changes in how work and work interactions are carried out. JD-R explains that technology can enhance wellbeing when it functions as a resource, but can also diminish it when it becomes a job demand. COR asserts that wellbeing depends heavily on the state of the resources an individual possesses. Research shows mixed results regarding this

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relationship. Some studies find a positive effect (Chuang et al., 2025; Valtonen et al., 2025), while others show a negative or non-significant effect (Giuntella et al., 2025; Routray et al., 2025). This inconsistency indicates that the direct relationship still needs to be re-examined. Thus, the hypothesis formulated is:
H4: Artificial intelligence adoption has an effect on employee wellbeing.

Task Optimization on Employee Wellbeing

Task optimization reflects work efficiency that can reduce workload and increase satisfaction. *Employee wellbeing* relates to a positive psychological state at work. JD-R explains that work efficiency is a resource that enhances motivation and wellbeing. COR further asserts that improved efficiency reflects an accumulation of individual resources. Research shows that task optimization has a positive effect on employee wellbeing (Chuang et al., 2025; Falco et al., 2023; Valtonen et al., 2025). As work becomes more efficient, employees experience reduced stress and greater job satisfaction. Thus, the hypothesis proposed is:
H5: Task optimization has a positive effect on employee wellbeing.

Workplace Safety on Employee Wellbeing

Workplace safety provides a sense of security that supports employees' psychological stability. *Employee wellbeing* increases when employees feel protected and work in a safe environment. JD-R explains that workplace safety is an important resource for enhancing wellbeing. COR asserts that a sense of security helps preserve individuals' psychological resources. Research shows that workplace safety contributes positively to wellbeing (Bankins et al., 2024; Ciccarelli, 2024; Falco et al., 2023). A safe working environment enables employees to work without excessive pressure. The following hypothesis can therefore be formulated:
H6: Workplace safety has a positive effect on employee wellbeing.

Techno-Overload on Employee Wellbeing

Techno-overload reflects pressure arising from excessive technology use. *Employee wellbeing* declines when individuals experience fatigue due to high job demands. JD-R explains that excessive job demands will reduce wellbeing. COR asserts that the loss of energy due to work pressure will negatively affect psychological condition. Research shows that techno-overload has a negative effect on wellbeing (Ragu-Nathan, 2023; Routray et al., 2025; Tarafdar et al., 2023). High technological burden increases employee stress and fatigue. Taking this into account, the

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hypothesis proposed is:
H7: Techno-overload has a negative effect on employee wellbeing.

The Mediating Role of Task Optimization, Workplace Safety, and Techno-Overload in the Relationship between Artificial Intelligence Adoption and Employee Well-being

Beyond its direct effects, *AI adoption* is expected to channel its influence on *employee well-being* indirectly through three mechanisms at once *task optimization*, *workplace safety*, and *techno-overload* as elaborated in the following three mediation hypotheses.

Within the JD-R framework, *task optimization* occupies the position of a *job resource* resulting from AI implementation, so that the effect of *AI adoption* on *employee well-being* is fundamentally indirect, being channeled first through changes in how work is carried out (Demerouti & Bakker, 2023). Roczniewska et al. (2021) show that unit-level resources affect wellbeing not directly, but through prior changes in productivity and task-completion quality, in line with Enholm et al. (2022), who describe the benefits of AI for individual outcomes as a second-layer effect that follows a shift in workflow. COR theory reinforces this logic: the addition of resources in the form of work efficiency becomes the main pathway determining psychological wellbeing, rather than the technological stimulus itself (Hobfoll et al., 2023). Based on this discussion, the hypothesis proposed is:
H8: Task Optimization mediates the effect of Artificial Intelligence Adoption on Employee Well-being.

Beyond reducing task burden, AI also acts as a *job resource* in the domain of workplace safety through monitoring, risk detection, and reduced human error (Ciccarelli, 2024). Falco et al. (2023) confirm that digital safety climate is related to employee wellbeing, so that the increased sense of security brought about by AI has the potential to translate into an improved psychological condition, consistent with JD-R, which positions both physical and psychological safety as a job resource (Roczniewska et al., 2021). COR theory adds that a sense of security is a resource that, once accumulated, strengthens individuals' psychological resilience in facing job demands (Hobfoll et al., 2023). Thus, the effect of *AI adoption* on *employee well-being* has the potential to be channeled indirectly through the strengthening of *workplace safety*. Based on this discussion, the hypothesis proposed is:
H9: Workplace Safety mediates the effect of Artificial Intelligence Adoption on Employee Well-being.

Unlike the two preceding mediators, which occupy the position of a job resource, techno-

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overload within the JD-R framework functions as a job demand that arises from the complexity of, and adaptation demands imposed by, AI systems (Tarafdar et al., 2023). When these demands exceed employees' adaptive capacity, COR theory explains that psychological resources (time, energy, and focus) become depleted, and it is this depletion rather than AI implementation directly that shapes employees' wellbeing (Hobfoll et al., 2023). Ragu-Nathan et al. (2023) show that technostress consistently serves as a pathway linking technological demands to a range of employee outcomes, whether interpreted as a burden or as a developmental challenge (Routray et al., 2025). This pathway is open to both directions, so techno-overload is expected to still mediate the effect of AI adoption on employee well-being regardless of the valence of its impact. Based on this discussion, the hypothesis proposed is:

H10: Techno-Overload mediates the effect of Artificial Intelligence Adoption on Employee Well-being.

Conceptual Framework

The conceptual framework of this study links five main constructs together with their theoretical sources, namely *Artificial Intelligence Adoption* (Dwivedi et al., 2023), *Task Optimization* (Robbins & Judge, 2017), *Workplace Safety* (Ciccarelli, 2024), *Techno-Overload* (Tarafdar et al., 2023), and *Employee Well-being* (Hansson et al., 2026). These five constructs are interrelated through ten hypotheses (H1-H10) as explained in the preceding subsections, with three mediating pathways (H8, H9, H10) linking *AI adoption* and *employee well-being* through *task optimization*, *workplace safety*, and *techno-overload*.

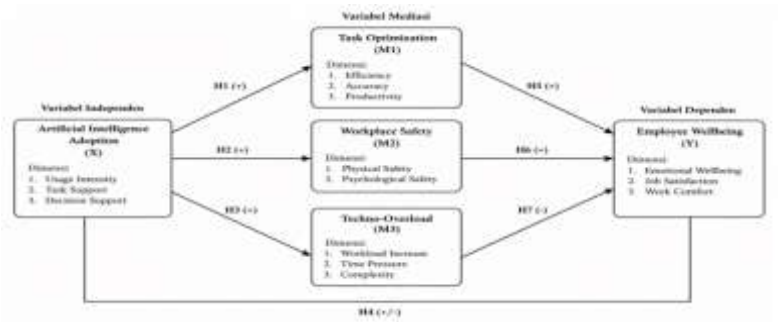


Figure 1. Research Conceptual Framework

RESEARCH METHOD

This study uses a quantitative approach aimed at explaining the relationships among the variables formulated in the research model. Data were collected through a questionnaire

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distributed to employees of Baitul Maal wat Tamwil (BMT) in the Purwokerto and Purbalingga areas. These locations were chosen because BMTs in both areas have begun adopting digital systems in their operations, making them relevant for examining the phenomenon of AI adoption in the context of Islamic microfinance institutions. The population of this study is all active BMT employees in the Purwokerto and Purbalingga area who have used or been exposed to digital/AI systems in their daily work, spread across 45 BMTs, with an estimated population size of ±440 people based on data from the Department of Cooperatives and SMEs (Dinas Koperasi dan UKM) of Banyumas and Purbalingga Regencies, combined with regional data from the Indonesian BMT Association (PBMTI), 2025. Because the exact population size cannot be fully identified and no complete sampling frame is available, the sampling technique used is non-probability sampling with a purposive sampling method, in which respondents are selected based on specific criteria, such as employees who have used or been exposed to digital/AI systems in their work (Sekaran & Bougie, 2016).

The sample size was determined based on the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which requires a minimum of 5-10 times the number of indicators used in the study (Hair et al., 2021). Given that the number of indicators in this study is estimated at around 25-30 items, the minimum sample size falls within the range of 125-300 respondents. To improve the reliability of the results, this study targeted a minimum of 150 respondents. Data were collected using a questionnaire instrument developed based on the indicators of each variable. Each statement item was measured using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). This scale was chosen because it can capture respondents' perceptions more flexibly and is commonly used in organizational behavior research (Likert, 1932).

The variables in this study consist of artificial intelligence adoption as the independent variable, task optimization, workplace safety, and techno-overload as mediating variables, and employee wellbeing as the dependent variable. Measurement indicators were adapted from prior research whose validity and reliability have been established, with adjustments made to the BMT context. AI adoption was measured based on the ability to use technology at work (Dwivedi et al., 2023), task optimization based on work efficiency and effectiveness (Valtonen et al., 2025), workplace safety based on the sense of security at work (Falco et al., 2023), techno-overload based on pressure arising from technology (Tarafdar et al., 2023), and employee wellbeing based on psychological condition and job satisfaction (Diener et al., 2018).

Data were analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach with the help of SmartPLS software. This method was chosen because it can

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accommodate a complex research model with mediating variables and does not require normally distributed data (Hair et al., 2021). The analysis was conducted in two stages: evaluation of the measurement model (outer model), covering validity and reliability testing, and evaluation of the structural model (inner model), to test the relationships among variables and the research hypotheses.

To anticipate bias particularly common method bias that may arise from the use of a single questionnaire this study applied several measures, such as constructing clear and unambiguous items and ensuring respondent anonymity so that answers would be more objective. In addition, statistical tests such as Harman's single factor test were used to ensure that bias did not dominate the data (Podsakoff et al., 2003).

Respondent Demographics

This study involved 338 respondents from various BMTs in the study area, with demographic profiles grouped by gender, age, length of service, and employment status, as summarized in Table 1.

Table 1. Respondent Demographic Profile

Demographic Characteristic	Category	Frequency (People)	Percentage (%)
Gender	Female	173	51.2
	Male	165	48.8
Age	20 - 25 years	55	16.3
	> 25 - 35 years	135	39.9
	> 35 - 45 years	109	32.2
	> 45 - > 50 years	39	11.5
Length of Service	< 1 year	30	8.9
	1 - 3 years	41	12.1
	3 - 5 years	74	21.9
	5 - 10 years	99	29.3
	> 10 years	94	27.8
Employment Status	Permanent employee	280	82.8
	Non-permanent employee	58	17.2
Total		338	100.0

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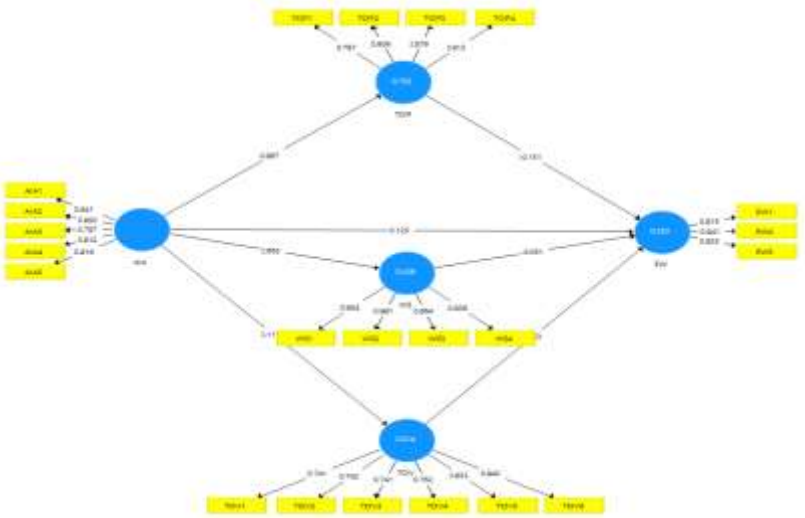
The gender distribution of respondents was relatively balanced (51.2% female; 48.8% male), which is important for ensuring that assessments of *techno-overload* and *task optimization* are measured objectively from both sides (Tarafdar et al., 2023). The majority of BMT staff are within the productive age range of 25-45 years (more than 72%); although generally adaptive, this group remains vulnerable to technological complexity, digital workload, and AI-adaptation demands within Islamic financial institutions (Bankins et al., 2024; Hasan, R., & Ali, 2023; Liu et al., 2024; Tarafdar et al., 2023).

Most respondents (57.1%) have five or more years of service, making them credible for assessing differences in *task optimization* between the conventional era and the post-digitalization era (Hasan, R., & Ali, 2023). The dominance of permanent employees (82.8%) also supports the evaluation of the JD-R model, since high job stability ensures that changes in subjective wellbeing are genuinely driven by technological pressure rather than by short-term employment-contract uncertainty (Califf et al., 2023).

RESULTS AND DISCUSSION

Measurement Model Evaluation (Outer Model)

Evaluation of the measurement model (*outer model*) is the first step in PLS-SEM analysis to ensure the validity and reliability of the instrument, covering discriminant validity, convergent validity (through *outer loading* and *Average Variance Extracted*/AVE), and internal consistency reliability (*Cronbach's Alpha* and *Composite Reliability*).



SEM-PLS Model Analysis Result

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Overall, the measurement model is very good: most indicators are above 0.70, indicating that respondents understood the questionnaire items consistently (Hair et al., 2021).

Convergent Validity

Convergent validity was assessed through the *outer loading* of each indicator and *Average Variance Extracted* (AVE), with an *outer loading* threshold of 0.70. Most indicators meet this standard, except AIA1 (an indicator of *Artificial Intelligence Adoption*) at 0.641; referring to Hair et al. (2021), indicators with loadings of 0.40-0.70 can still be retained as long as their removal does not significantly increase AVE and Composite Reliability, so AIA1 was retained for the subsequent testing stage.

Table 2. Indicator Outer Loading Values

Indicator	Questionnaire Item	AIA	EW	TOP	TOV	WS
AIA1	Frequently uses digital/AI systems in daily work routines	0.641				
AIA2	Digital/AI systems help complete administrative tasks faster	0.850				
AIA3	Relies on AI data/analysis for operational decisions and customer service	0.797				
AIA4	Job responsibilities are highly dependent on the smooth operation of the system/AI	0.812				
AIA5	Digital/AI systems are integrated into almost all work activities	0.816				
EW1	Feels emotionally comfortable with the work routine and environment		0.815			
EW4	Working at the BMT provides a positive emotional feeling (happiness)		0.841			
EW5	Has a good balance between work life and personal life		0.835			

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TOP1	Digital technology speeds up completion of work targets			0.787		
TOP2	Work systems/applications reduce calculation/recording errors			0.909		
TOP3	Automation systems improve the quality and accuracy of work output			0.879		
TOP4	Technology enables handling more tasks/customers optimally			0.813		
TOV1	New digital systems add to workload and reporting volume				0.741	
TOV2	System speed forces responses to tasks at too fast a pace				0.742	
TOV3	Difficulty and being overwhelmed by continuous adaptation to system updates				0.741	
TOV4	Continuous interaction with digital systems feels mentally burdensome				0.742	
TOV5	The system demands multitasking beyond a comfortable limit				0.833	
TOV6	Chasing system targets triggers daily stress and pressure				0.840	
WS1	Digital systems create a feeling of safety from fatal operational risk					0.854
WS2	Monitoring systems make the workflow more structured and controlled					0.881
WS3	AI system protection provides peace of mind regarding error sanctions					0.862
WS4	Technology creates a stable work environment, reducing anxiety					0.836

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Table 2 confirms that all indicators, including AIA1, meet the required convergent-validity criteria.

Construct Reliability and Discriminant Validity

Construct reliability was tested through *Composite Reliability* (CR), *Cronbach's Alpha*, and *rho_A*, with a threshold of 0.70 indicating strong stability and minimal random error.

Convergent validity was also tested through AVE, with a threshold of 0.50 (Hair et al., 2021). The results of the construct reliability and validity tests are presented in Table 3.

Table 3. Construct Reliability and Validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Artificial Intelligence Adoption	0.844	0.865	0.889	0.619
Employee Wellbeing	0.777	0.781	0.870	0.690
Task Optimization	0.869	0.875	0.911	0.720
Techno-Overload	0.870	0.887	0.901	0.605
Workplace Safety	0.882	0.883	0.918	0.738

Table 3 shows that all constructs have very good reliability (Cronbach's Alpha and CR above 0.70) and adequate convergent validity (AVE above 0.50) (Hair et al., 2021).

Table 4. Discriminant Validity Matrix (Fornell-Larcker)

Construct	AIA	EW	TOP	TOV	WS
AIA	0.786				
EW	0.047	0.831			
TOP	0.867	0.028	0.848		
TOV	0.117	0.736	0.142	0.778	
WS	0.663	0.067	0.701	0.188	0.859

Table 4 shows that the *Fornell-Larcker* criterion (the square root of AVE on the diagonal) is met for most constructs, except for the relationship between *Artificial Intelligence Adoption* (AIA)

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and *Task Optimization* (TOP): their correlation (0.867) exceeds the square root of AVE for each (AIA = 0.786; TOP = 0.848), a result that is conceptually understandable, since task optimization is a direct consequence of AI implementation in the workplace. To further ensure discriminant validity, the more sensitive *Heterotrait-Monotrait Ratio* (HTMT) criterion was also used (Hair et al., 2021); the results show that the HTMT value between AIA and TOP remains below the 0.90 threshold, so each latent variable is confirmed to have distinct empirical characteristics without problematic measurement overlap. Thus, despite a minor note on the Fornell-Larcker criterion, the research instrument is deemed to satisfy discriminant validity and is fit to proceed to structural model (*inner model*) analysis.

Structural Model Evaluation (Inner Model) and Hypothesis Testing

Model Fit Test

Before hypothesis testing, model fit was checked to ensure that the chosen structure adequately reflects the data by comparing the *saturated* model (in which all variables are freely interconnected) with the *estimated* model (the structure adjusted to the research hypotheses), as summarized in Table 5.

Table 5. Model Fit Test Results

Criterion	Saturated Model	Estimated Model
SRMR	0.079	0.087
d_ULS	1.574	1.914
d_G	n/a	n/a
Chi-Square	n/a	n/a
NFI	n/a	n/a

The SRMR value of 0.079 (saturated) and 0.087 (estimated) slightly exceeds the strict 0.08 threshold but remains below 0.10, which is commonly considered acceptable in PLS-SEM (Hair et al., 2021); the d_ULS values (1.574 and 1.914) are classified as *exact fit* measures, ideally interpreted through *bootstrapping*. As for d_G, Chi-Square, and NFI, these are reported as n/a, which is common in PLS-SEM models with complex mediating structures, given that SRMR is already sufficient as the primary fit indicator, while Chi-Square and NFI designed for *covariance-based* SEM (CB-SEM) and are less appropriate when rigidly applied to PLS-SEM (Hair et al., 2021). Overall, the model fit test results indicate that the model is suitable for hypothesis testing.

Direct-path hypothesis testing used the *bootstrapping* method to evaluate the *path*

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coefficient, *T-statistics*, and *p-values*, with results summarized in Table 6.

Table 6. Hypothesis Testing Results (Total Effects)

Hypothesis	Path	Path Coefficient	T-Statistics	P-Values	Decision
H1	AIA → TOP	0.867	58.191	0.000	Accepted
H2	AIA → WS	0.663	16.803	0.000	Accepted
H3	AIA → TOV	0.117	2.189	0.015	Accepted
H4	AIA → EW	0.125	1.668	0.048	Rejected
H5	TOP → EW	-0.151	1.976	0.024	Rejected (opposite direction)
H6	WS → EW	-0.051	1.037	0.150	Rejected
H7	TOV → EW	0.753	27.465	0.000	Rejected (opposite direction)

The effect of AI adoption on task optimization, workplace safety, and techno-overload is significant and in the predicted direction, while the direct effect of AI adoption and of workplace safety on employee well-being is not statistically significant. Meanwhile, task optimization and techno-overload both have a significant effect on employee well-being, but in a direction opposite to the initial prediction: *task optimization* has a negative impact on *employee well-being* (β = -0.151), while *techno-overload* actually has a positive impact (β = 0.753) indicating a paradox in the implementation of AI at Islamic microfinance institutions.

Table 7. Mediation Effect Testing (Specific Indirect Effects)

Mediation Path	Original Sample (O)	T-Statistics	P-Values	Result
AIA → TOP → EW	-0.131	1.825	0.034	Significant
AIA → TOV → EW	0.088	2.057	0.020	Significant
AIA → WS → EW	-0.034	1.020	0.154	Not Significant

Task optimization and *techno-overload* are proven to significantly mediate the effect of *AI adoption* on *employee well-being* ($p < 0.05$), while mediation through *workplace safety* is not significant ($p > 0.05$).

This pattern in Table 7 reinforces the findings from the direct-path testing above: *task optimization* emerges as a detrimental mediating pathway (negative direction), while *techno-*

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overload emerges as a beneficial mediating pathway (positive direction). Both results confirm that the effect of *AI adoption* on *employee well-being* is fundamentally indirect and is channeled through changes in the way work is carried out as well as the psychological burden employees experience, rather than functioning as a stand-alone stimulus. The non-significant mediation through *workplace safety* indicates that the improved sense of security brought about by AI stops at the level of a baseline-condition improvement and has not yet been strong enough to translate into deeper psychological wellbeing gains among BMT employees. An in-depth interpretation of all three mediating pathways is elaborated further in the Discussion section below.

Structural model evaluation also includes R Square (R^2), which shows the proportion of variance in an endogenous construct explained by its predictors, as well as Adjusted R Square, which is corrected for the number of predictors and sample size. A summary of both values for each endogenous construct is presented in Table 8.

Table 8. R Square and Adjusted R Square Values

Construct	R Square	Adjusted R Square
Task Optimization	0.752	0.751
Workplace Safety	0.439	0.438
Techno-Overload	0.014	0.011
Employee Wellbeing	0.553	0.547

Following the categorization of Hair et al. (2021), an R^2 of 0.75 is considered strong, 0.50 moderate, and 0.25 weak. *Task Optimization* recorded the highest R^2 (0.752) *AI adoption* explains 75.2% of its variance, consistent with the large path coefficient from AI adoption to task optimization ($\beta = 0.867$) and confirming AI as the primary determinant of task optimization at BMT. *Employee Well-being* obtained a moderate R^2 (0.553), meaning its four predictors jointly explain 55.3% of the variance in employee wellbeing, with the remaining 44.7% influenced by factors outside the model, such as leadership or compensation. *Workplace Safety* recorded an R^2 of 0.439, close to the moderate category. The most notable finding comes from *Techno-Overload*, which obtained only an R^2 of 0.014 (very weak) even though the path from *AI adoption* to *techno-overload* is statistically significant, AI explains only 1.4% of its variance, with the remaining 98.6% determined by other factors such as digital literacy or personality. This gap reinforces the argument that techno-overload is more appropriately understood as an individual psychological phenomenon rather than a dominant consequence of AI alone. The very small difference between

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R^2 and Adjusted R^2 (0.001-0.006) across all constructs indicates that the model is stable and not overfitted.

DISCUSSION

This section discusses how AI implementation at BMT, through the mechanisms of *task optimization*, *workplace safety*, and *techno-overload*, affects *employee well-being*, while also illustrating how digital transformation influences employees' mental health within a socio-religious organization.

The Effect of AI Adoption on Task Optimization

The test results confirm that AI use significantly accelerates work processes, in line with this study's initial prediction (Hansson et al., 2026; Noy & Zhang, 2023). Within the JD-R framework, AI functions as a *job resource* that enables BMT to achieve real *task optimization*, consistent with the two-sided view of AI as a tool that brings both benefits (efficiency) and risks (cognitive pressure) (Vrontis et al., 2022). This finding aligns with literature showing that AI drives functional automation and cuts routine work (Dwivedi et al., 2023; Hannigan, 2024), reduces task-completion time (Noy & Zhang, 2023), and eases workflow through a *complementary effect* (Raisch & Krakowski, 2021; Vrontis et al., 2022). For BMT staff, this acceleration is tangible in day-to-day administrative work and customer service: recording and verification tasks that once took considerable time can now be completed far more quickly, freeing employees to focus more of their attention on aspects of the job that require judgment and human interaction. This suggests that, when implemented appropriately, AI can act as an efficiency catalyst without automatically displacing employees' strategic role within a trust-based organization such as BMT. The results of this study indicate that the high level of reliance on and frequency of AI use in various work activities to expedite task completion and support decision-making have been shown to significantly minimize work errors and improve employee quality and productivity, according to Chuang et al. (2025); Robbins & Judge. (2017); Valtonen et al. (2025).

The Effect of AI Adoption on Workplace Safety

The test results also confirm that AI significantly improves workplace safety, in line with this study's prediction (Vrontis et al., 2022), and consistent with the JD-R concept, which views AI as a *job resource* that reduces the likelihood of negligence through automated monitoring (Chowdhury et al., 2023; Ciccarelli, 2024). This finding again confirms AI's two-sided pattern

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bringing benefits (efficiency, protection) alongside risks (mental pressure) and is consistent with research showing AI's ability to process big data for early detection of threats and risks (La Torre et al., 2026). For BMT, workplace safety is crucial for preventing operational risks such as fraud and calculation errors; AI has been shown to reduce such risks within the context of Indonesia's sharia economy (Rahayu, 2023), while also providing both physical and psychological security (Vrontis et al., 2022) by easing staff's burden with complex tasks (Budhwar et al., 2022). Built-in early-warning and automatic-validation features in work applications also help staff avoid administrative errors that could otherwise result in sanctions or financial loss, allowing employees to carry out both operational duties and customer service with greater calm and confidence. The findings of this study indicate that high levels of usage and reliance on AI systems to streamline tasks and support work-related decisions have been shown to create controlled operational workflows, reduce the risk of critical errors, and foster a stable and safe work environment, according to Ciccarelli. (2024); Falco et al. (2023).

The Effect of AI Adoption on Techno-Overload

The test results show that AI use has a significant effect on increasing *techno-overload*, consistent with this study's prediction. In line with JD-R, the complexity of AI systems triggers new job demands that drain energy and induce stress (Demerouti & Bakker, 2023): BMT staff often feel overwhelmed by the volume of AI-generated data, which still requires manual checking, forcing employees to run digital and manual workflows simultaneously and thereby adding to their daily workload (Chang et al., 2024). This darker side of digital transformation has also been found in other financial-sector contexts, where the pace of service automation often outstrips human readiness (Kim et al., 2025), forcing staff into high-tempo multitasking (Liţan, 2025) that leads to cognitive fatigue (Tarafdar et al., 2023). This is consistent with COR theory: individuals' energy, time, and focus become depleted due to the constant demand to learn and adapt to new systems (Hobfoll et al., 2023), so that a shortage of psychological resources triggers exhaustion and elevated techno-overload in the workplace (Routray et al., 2025). This finding should nonetheless be read with care, since such burden does not automatically translate into a negative outcome for every employee, as clarified further in the discussion of techno-overload's effect on employee wellbeing below. The findings of this study indicate that the high frequency and reliance on AI to expedite tasks and support work-related decisions can, in fact, lead to stress, according to Ragu-Nathan et al. (2023; Tarafdar et al. (2023).

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The Direct Effect of AI Adoption on Employee Wellbeing

The test results show that the direct effect of *AI adoption* on *employee well-being* is not significant, running counter to this study's initial prediction (Asmini, 2025) AI does not automatically improve the wellbeing of BMT employees. This finding aligns with the pattern of uncertainty found in prior studies, although Shaik et al. (2023) propose that AI improves *well-being* by improving working conditions, since AI's effect on performance tends to vary depending on the scale of analysis, the role of the workforce, and the industry sector (Pereira et al., 2023). *Self-Determination Theory* (SDT) further confirms that there is no fixed link between the intensity of tool use and a sense of enjoyment (Gagné et al., 2022; Routray et al., 2025). This is because AI's effect on wellbeing is indirect, emerging only after a prior shift in workflow (Enholm et al., 2022) and requiring mediators such as job security, task improvement, or technological burden (Asmini, 2025; Gagné et al., 2022). This mediating pattern is even more central at BMT, given that these institutions rely on strong relationships, personal closeness, and Islamic values in every interaction (Asmini, 2025). In other words, the mere presence of technology is not enough to make employees feel better off; what matters is how that technology reshapes their everyday work experience. The results of this study indicate that the high frequency and reliance on AI use have not yet been able to accelerate task completion or support work-related decision-making outcomes that are expected to align with the creation of a sense of comfort, happiness, and satisfaction, while also maintaining employees' motivation, sense of meaning in work, and work-life balance with minimal stress levels, according to Diener et al. (2018); Dwivedi et al. (2023); Valtonen et al. (2025).

The Paradox of Task Optimization on Employee Wellbeing

Theoretically, work efficiency should improve *employee well-being* (Valtonen et al., 2025), yet this study instead finds that *task optimization* has a negative effect on *employee well-being*, statistically significant but running counter to this study's initial prediction. AI-based optimization often adds burden, strips tasks of meaning, and reshapes the workspace (Dima et al., 2024; Parker & Grote, 2023; Soulami et al., 2024), eroding the human interaction that is especially crucial in BMT's distinctive relational culture (Hasan, R., & Ali, 2023). From a socio-technical systems perspective, automated systems regulate the pace of tasks and narrow employees' room for maneuver, positioning staff as passive operators (Parent-Rocheleau & Parker, 2022; Parker & Grote, 2023) a condition that hinders the fulfillment of the need for *relatedness*, which, according to Self-Determination Theory, is crucial for wellbeing. This paradox is consistent with the idea that AI's effect is highly context-dependent (Pereira et al., 2023): AI at BMT has so far only delivered a

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first-layer effect (efficiency gains) but has yet to progress to a second-layer effect in the form of improved psychological condition (Enholm et al., 2022). Ironically, the more optimally AI restructures work, the less room remains for the informal conversation, mutual help, and shared moments that have long characterized BMT's work culture. BMT management therefore needs to balance digital optimization with a strengthening of human values, so that digital transformation does not come at the expense of staff wellbeing (Trenerry et al., 2021). The results of this study indicate that improving work quality and productivity through faster task completion and fewer errors is expected to foster a sense of comfort, satisfaction, and happiness among employees, while also maintaining motivation, a sense of meaning in work, work-life balance, and minimizing stress, according to (Diener et al., 2018; Robbins & Judge, 2017; Valtonen et al., 2025).

The Role of Workplace Safety on Employee Wellbeing

The link between *workplace safety* and *employee well-being* is not significant and even tends to run counter to this study's initial prediction. Participants appear to view AI-based protection merely as a baseline standard that alleviates technical concerns (Falco et al., 2023), without being strong enough to drive inner satisfaction. Referring to JD-R, more vibrant elements of work coworker support, social relationships, and open leadership play a far greater role in boosting wellbeing than the mere fulfilment of routine safety standards (Roczniewska et al., 2021). If subtler psychosocial hazards are neglected, technical protection alone carries little meaning (Schulte et al., 2024): isolation, loss of control, and a piling-up of tasks can still trigger burnout even when the physical workplace is safe (Amoadu et al., 2024). In other words, the sense of security provided by the system is simply a baseline need that, once met, no longer feels distinctive, while deeper needs such as recognition, relatedness, and meaning at work remain untouched by AI-based safety investment alone. Workplace safety therefore needs to be broadened beyond preventing equipment accidents toward a comprehensive redesign of work management (Schulte et al., 2024); without addressing the psychological governance of work, its effect on wellbeing tends to remain unstable (Javanmardi et al., 2025), making a multi-faceted strategy for redesigning the workspace essential (Amoadu et al., 2024). The results of this study indicate that the creation of controlled workflows, a stable environment, and a sense of security from the risk of fatal errors is expected to foster a sense of comfort, happiness, and satisfaction among employees, while also minimizing stress and maintaining motivation, a sense of meaning in work, and work-life balance, according to (Ciccarelli. (2024); Diener et al. (2018); Falco et al. (2023).

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The Positive Effect of Techno-Overload on Employee Wellbeing

Although digital burden is generally viewed as a risk (Ragu-Nathan, 2023), this study finds that *techno-overload* actually has a positive effect on *employee well-being*, statistically significant but running counter to this study's initial prediction. *Eustress* theory ('good stress') explains this condition: BMT staff interpret adaptation demands as opportunities to grow, rather than as a *hindrance stressor*. *Workplace Psychosocial Hazard* (WPH) in the form of task overload, time pressure, and adaptation complexity generally triggers fatigue and declining mental health (Amoadu et al., 2024; Dhakal & Mahmood, 2025), yet the demand to master AI is instead viewed by staff as a path to gaining expertise amid fintech disruption (Liu et al., 2024; Routray et al., 2025), providing a sense of accomplishment, career stability, and recognition. For some staff, the ability to operate AI systems even becomes a source of personal pride and an asset for future career development. This shift from burden to enthusiasm depends on psychological safety in the workplace, which is built through open communication and supportive leadership (Ip et al., 2025), as well as comprehensive organizational measures that ensure technological pressure becomes a driver of growth rather than a source of alienation (Aust et al., 2023), including the provision of adequate work tools and a supportive psychosocial atmosphere (Amoadu et al., 2024; Aust et al., 2023). The results of this study indicate that technology-related stress characterized by an increased workload, demands for speed, the need to multitask, and difficulty adapting to systems has the potential to disrupt employee well-being by reducing comfort, satisfaction, and job happiness, as well as triggering stress that impacts motivation, the meaning of work, and work-life balance, according to Diener et al. (2018; Ragu-Nathan et al. (2023).

Task Optimization as a Detrimental Mediator in the Relationship between AI Adoption and Employee Wellbeing

Mediation testing shows that the mediating role of *task optimization* in channeling the effect of *AI adoption* on *employee well-being* is significant in a negative direction. This confirms that the effect of *AI adoption* on *employee well-being* is indeed channeled through *task optimization*, but in a detrimental way that runs counter to the general assumption of JD-R (Roczniewska et al., 2021). This pattern is consistent with the earlier finding that AI strongly drives *task optimization*, while *task optimization* itself actually suppresses *well-being*: the more optimally AI restructures work at BMT, the greater the risk of eroding human interaction and the meaning of work (Hasan, R., & Ali, 2023; Parker & Grote, 2023). From a socio-technical systems perspective, algorithmic optimization tends to dictate the pace of work and narrow employees' room for

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maneuver, turning them into passive operators (Parent-Rocheleau & Parker, 2022), while continuous AI system updates add adaptation burden and strip tasks of their subjective meaning (Dima et al., 2024) this combination explains why task optimization becomes a detrimental mediating pathway for BMT staff's wellbeing: the efficiency gains visible on the surface carry a hidden psychological cost that only becomes apparent once the mediating pathway is traced. The results of this study indicate that although the high frequency and reliance on AI use have been shown to increase productivity and work quality through faster task completion and fewer errors, this optimization actually risks harming employee well-being by triggering stress, disrupting work-life balance, and reducing comfort, satisfaction, happiness, and a sense of meaning in work, according to Diener et al. (2018); Dwivedi et al. (2023).

Workplace Safety Fails to Mediate the Relationship between AI Adoption and Employee Wellbeing

Unlike the other two pathways, the mediating role of *workplace safety* is not significant, consistent with the earlier finding that *workplace safety* also has no significant direct effect on *employee well-being*. Even though AI is proven to strongly improve workplace safety, this improvement appears to stop at the level of a baseline-condition improvement and does not translate into psychological wellbeing (Falco et al., 2023). Within the JD-R framework, *workplace safety* appears to function as a hygiene-type *job resource* meeting the minimum requirement for a sense of security, but not strong enough to serve as a motivational source that carries further through to *well-being* (Roczniewska et al., 2021). This finding clarifies that the effect of *AI adoption* on *employee well-being* at BMT is driven more by changes in the meaning and demands of work than by improvements in the safety aspect alone, so digital-security investment should not be treated as a stand-alone strategy for employee wellbeing. The results of this study indicate that although the high frequency and reliance on AI have proven capable of creating a controlled work system and minimizing the risk of fatal errors, the sense of security and stability in the work environment are, in fact, not strong enough to boost employee well-being in terms of comfort, satisfaction, happiness, or a sense of meaning in work, according to Diener et al. (2018); Falco et al. (2023); Valtonen et al. (2025).

Techno-Overload as a Positive Mediator in the Relationship between AI Adoption and Employee Wellbeing

Testing of the mediating role of *techno-overload* proves significantly positive. This finding

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complements the earlier results showing that AI increases *techno-overload* and that *techno-overload* has a positive effect on *well-being*, demonstrating that this pathway genuinely channels the effect of *AI adoption* on employee wellbeing, rather than being merely an isolated direct effect. Consistent with the *eustress* perspective, BMT staff interpret AI adaptation demands as a challenge that spurs competence rather than a threat (Routray et al., 2025; Tarafdar et al., 2023): underpinned by adequate psychological safety and organizational support, this pressure turns into an experience that fosters a sense of accomplishment and career stability (Amoadu et al., 2024; Ip et al., 2025), provided the organization supplies adequate work tools and a supportive psychosocial atmosphere (Aust et al., 2023). Together with the mediating role of task optimization, this result stands as the central evidence for this study's dual mechanism: *task optimization* as a detrimental mediating pathway, and *techno-overload* as a beneficial mediating pathway both significant, yet opposite in direction while *workplace safety* plays no mediating role at all. This underscores that the success of digital transformation at BMT cannot be measured solely by the degree of efficiency achieved, but also by how employees make sense of that change in their everyday work. The results of this study indicate that the high frequency and reliance on AI to expedite tasks do indeed create a technological burden in the form of increased workload, the need for multitasking, and demands for system speed; however, this pressure actually has a positive impact, as it has been shown to boost motivation, give meaning to work, and enhance employees' sense of comfort, happiness, and job satisfaction, according to Diener et al. (2018); Ragu-Nathan et al. (2023); Tarafdar et al. (2023); Valtonen et al. (2025).

CONCLUSION

This study examines the effect of *AI adoption* on *employee well-being* among BMT employees in Purwokerto and Purbalingga through *task optimization*, *workplace safety*, and *techno-overload* as mediating mechanisms, integrating Job Demands-Resources (JD-R) and Conservation of Resources (COR) theory. The results reveal a complex pattern that partly contradicts the initial theoretical assumptions.

AI adoption has a positive and highly significant effect on all three mediators, while its direct effect on *employee well-being* is not significant. This is an important starting point: AI adoption at BMT genuinely changes the way work is carried out, yet that change is not automatically felt as improved psychological wellbeing *AI adoption* only becomes meaningful for *well-being* after passing through certain intermediaries.

Two findings stand out. First, *task optimization*, which would ideally improve wellbeing,

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instead has a negative effect, because high work efficiency erodes human interaction and reduces the subjective meaning of work. Second, *techno-overload*, commonly seen as a source of pressure, instead has a positive effect, because staff interpret AI-adaptation demands as *eustress* a challenge that spurs competence rather than a threat. *Workplace safety* has no significant effect, being viewed more as a baseline standard than a source of satisfaction. Mediation testing reinforces this pattern: *task optimization* and *techno-overload* significantly mediate the effect of *AI adoption* on *well-being* in opposite directions, while *workplace safety* does not mediate at all.

Theoretically, these findings show that a *job resource* does not always benefit *well-being*, a *job demand* such as *techno-overload* is not always detrimental when interpreted as a challenge, and the psychological meaning employees attach to technological change matters as much as the job demands-resources structure itself.

Practically, BMT management cannot rely on technical efficiency alone as a benchmark for successful digital transformation. *Task optimization* pursued without strengthening coworker interaction risks eroding staff wellbeing, so management should deliberately preserve space for human interaction and manage AI-adaptation demands through training, open communication, and recognition. BMT are advised to run a structured, ongoing *AI adoption training* program covering technology literacy, digital-competence building, and psychological support during system transitions, as a key strategy for balancing digital efficiency with employees' long-term psychological wellbeing.

SUGGESTIONS

This study has several limitations that should be noted. First, the sample is limited to BMT employees in the Purwokerto and Purbalingga area, so generalizing the results to other regions or other types of Islamic microfinance institutions should be done with caution. Second, the research design is *cross-sectional*, so it cannot capture the dynamics of change in *employee well-being* over the course of the AI-adoption process. Third, data were collected through a *self-report* questionnaire, which carries the potential for perception bias, although this was anticipated through *Harman's single factor test*.

Based on these limitations, future research is encouraged to: (1) use a *longitudinal* design to trace changes in *task optimization*, *techno-overload*, and *employee well-being* over time; (2) extend the sample coverage to BMT in other regions or to Islamic microfinance institutions across countries to test the generalizability of the *dual-mechanism* model; (3) test moderating variables such as leadership style, digital literacy, or organizational support to clarify the conditions that

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strengthen or weaken the *eustress* effect of *techno-overload*; and (4) incorporate a qualitative approach to explore in depth the psychological meaning BMT employees attach to digital transformation. For BMT management, it is recommended to periodically evaluate the effectiveness of the AI-adoption training program and provide feedback channels for employees, so that digitalization policy remains responsive to staff's psychosocial needs.

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