

Artificial Intelligence Integration and Employee Turnover Intention: The Roles of Technostress and Reskilling Training

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ABSTRACT

The adoption of artificial intelligence and automation in the workplace has the potential to improve efficiency while also influencing employees' psychological and behavioral responses. Although reskilling training is expected to support employee adaptation to technological change, its effectiveness in shaping employee responses toward AI-driven transformation remains unclear. This study examines the direct effect of artificial intelligence integration on turnover intention, the mediating role of technostress, and the moderating role of reskilling training. A quantitative approach was employed using Structural Equation Modeling with SmartPLS 4. Data were collected through an online survey involving 265 employees working in organizations that had adopted artificial intelligence and automation technologies. The results showed that artificial intelligence integration had a significant positive effect on turnover intention, while its effect on technostress was positive but statistically insignificant. Furthermore, technostress did not significantly mediate the relationship between artificial intelligence integration and turnover intention. Reskilling training also did not significantly moderate the relationship between artificial intelligence integration and turnover intention or between technostress and turnover intention. These findings indicate that AI integration may influence turnover intention through mechanisms beyond technological strain, while reskilling training alone was not empirically confirmed as a significant buffering resource in this research context. This study contributes to the AI and employee management literature by highlighting the complexity of employee responses to AI-integrated workplaces and emphasizing the importance of broader organizational support strategies in managing technological transformation.

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1. INTRODUCTION

Digital transformation driven by Artificial Intelligence (AI) and automation has fundamentally reshaped contemporary workplaces, influencing organizational processes, decision-making systems, and human resource management practices. The increasing adoption of AI-based technologies enables organizations to enhance operational efficiency, improve analytical capabilities, and support more data-driven decision-making processes (Ekuma, 2024). However, AI integration also represents a significant transformation of employees' work environments because individuals are required to interact with new technological systems, develop new competencies, and adapt to changing patterns of work organization (Yusoh et al., 2021). Therefore, AI adoption should not only be understood as a technological advancement but also as an organizational change process that may influence employees' psychological experiences and workplace behaviors (Al-Surmi et al., 2022; Bris et al., 2021).

One emerging concern associated with AI-driven workplace transformation is algorithmic anxiety, which refers to employees' concerns regarding the increasing influence of algorithm-based systems on work decisions, job responsibilities, and future career prospects (Rudiyanto et al., 2023). Employees may experience uncertainty when algorithmic systems become increasingly involved in evaluating performance, allocating tasks, or supporting managerial decisions, particularly when these systems are perceived as complex, opaque, or difficult to control (Mathews et al., 2022). However, algorithmic anxiety represents a broader phenomenon describing employees' psychological concerns in algorithmic workplaces rather than an empirically measured construct in this study (Arnold et al., 2023). Instead, this research examines AI integration as an observable organizational change that may influence employees' attitudes and behavioral intentions. This distinction is important because understanding employees' responses to AI requires examining the specific mechanisms through which

technological transformation affects workplace outcomes.

Previous studies have primarily emphasized the operational advantages of AI adoption, including productivity improvement, decision-making efficiency, and organizational competitiveness (Vallas et al., 2022). Nevertheless, less attention has been devoted to understanding how AI integration influences employee retention-related outcomes, particularly turnover intention (Bankins et al., 2024). While technological transformation may create opportunities for employees to enhance their work capabilities, it may also introduce new demands related to learning requirements, adaptation pressures, and uncertainty regarding future job roles (Westphal et al., 2022). Therefore, an important research question remains regarding whether and how AI integration contributes to employees' intention to leave their organizations.

The Job Demands-Resources (JD-R) theory provides a suitable theoretical perspective for explaining employee responses to AI-integrated workplaces (Nguyen et al., 2023). JD-R theory proposes that every occupation consists of job demands and job resources, where excessive job demands may generate psychological strain when employees lack sufficient resources to cope with workplace challenges (Cramarenco et al., 2023). In the context of AI adoption, AI integration may function as an emerging technological job demand because employees are required to continuously acquire new knowledge, adjust to algorithm-driven processes, and modify established work practices. When employees perceive these technological demands as exceeding their available coping resources, they may experience negative psychological responses, including technostress.

Technostress refers to psychological strain experienced by individuals when they encounter difficulties in adapting to technological changes and new digital work requirements (Orieno et al., 2024). Within the JD-R framework, technostress can be considered a strain outcome resulting from increased technological demands that are not adequately balanced by available organizational resources. Previous studies indicate that technostress may reduce employees' psychological well-being, job satisfaction, and organizational attachment, potentially increasing their intention to seek alternative employment opportunities (Budhwar et al., 2022). However, despite growing attention toward technostress in digital workplaces, limited research has examined whether technostress explains the relationship between AI integration and turnover intention, particularly in organizations that have already adopted AI-based technologies.

Beyond examining technostress as a potential explanatory mechanism, this study also investigates the role of reskilling training as an organizational resource that may influence employees' adaptation to AI-driven workplace changes. Reskilling training provides employees with opportunities to develop new technological competencies and increase their readiness to work alongside emerging technologies (Agarwal et al., 2024). According to JD-R theory, organizational resources can reduce the negative effects of demanding work conditions by strengthening employees' ability to cope with workplace challenges (Asfahani, 2022). Therefore, reskilling training may function as a resource that helps employees manage AI-related demands and potentially reduces negative workplace outcomes. However, whether reskilling training is sufficient to alter employees' responses toward AI integration remains an important empirical question, as employee reactions may involve broader psychological and organizational considerations beyond skill development alone.

Despite increasing research interest in AI and workplace transformation, several important gaps remain. First, existing literature has not sufficiently clarified whether AI integration influences turnover intention directly or primarily through psychological mechanisms such as technostress. Second, although technostress has been widely discussed as an outcome of technological change, limited empirical evidence explains its mediating role in the relationship between AI integration and employee turnover intention. Third, while reskilling training is frequently proposed as an effective organizational response to technological disruption, its effectiveness as a mechanism for changing employees' reactions toward AI adoption remains insufficiently explored.

To address these gaps, this study contributes to the AI and human resource management literature in three important ways. First, it examines the direct relationship between AI integration and employee turnover intention, extending previous research that has largely focused on technological benefits rather than employee retention outcomes. Second, it investigates technostress as a mediating mechanism to explain how AI integration may influence employees' intention to leave their organizations. Third, it examines reskilling training as a moderating factor to determine whether organizational learning resources can influence employees' responses to AI-driven workplace transformation.

By integrating these relationships within the JD-R theoretical framework, this study provides a more comprehensive understanding of employee adaptation in AI-integrated workplaces. Rather than assuming that AI adoption inevitably produces negative employee outcomes, this research examines the specific conditions under which AI integration may influence turnover intention and whether organizational resources can shape employees' responses to technological change.

Although algorithmic anxiety represents the broader phenomenon motivating this investigation, this study empirically focuses on AI integration because it reflects the observable organizational transformation experienced by employees. Therefore, this research aims to investigate how AI integration affects employee turnover intention,

with technostress serving as a mediating mechanism and reskilling training functioning as a moderating factor. Specifically, this study seeks to understand whether AI-driven workplace transformation creates psychological demands that influence employees' decisions to remain with or leave their organizations, as well as whether organizational resources can support employee adaptation. Through this investigation, the study provides insights into the psychological and organizational dynamics of workforce sustainability in increasingly AI-integrated workplaces.

Literature Review and Hypotheses Development

Job Demands-Resources (JD-R) Theory

The increasing integration of Artificial Intelligence (AI) and automation represents a fundamental transformation in contemporary job design and organizational environments. To explain how employees respond to this transformation, this study adopts Job Demands-Resources (JD-R) Theory as its primary theoretical framework (Tummers & Bakker, 2021). JD-R Theory distinguishes between job demands, which require sustained physical, cognitive, or psychological effort, and job resources, which facilitate goal achievement, reduce the costs associated with job demands, and support employees' development and adaptation. Employee outcomes therefore depend partly on how employees experience workplace demands relative to the resources available to manage those demands (Lee, 2021).

AI and automation integration refers to the strategic incorporation of intelligent technologies and automated processes into organizational tasks, decision-making processes, and workflows (Sarath Kumar Boddu et al., 2022). Although AI integration can improve organizational efficiency and decision-making capabilities (Poon et al., 2022), it may simultaneously introduce new technological demands for employees. Employees may need to acquire new competencies, adjust established work routines, interact continuously with algorithm-based systems, and respond to changes in task allocation and job roles. From the JD-R perspective, these requirements can be conceptualized as technological job demands because they require sustained cognitive and psychological effort. When such demands exceed employees' perceived capacity to adapt, negative psychological responses may emerge.

Within this broader context, algorithmic anxiety describes employees' concerns about the increasing influence of algorithmic technologies on their work, roles, and future employment. In this study, however, algorithmic anxiety is not treated as an empirically measured construct. Rather, it represents the broader phenomenon motivating the examination of employees' responses to AI-integrated workplaces. The empirical model specifically focuses on AI and automation integration as the technological job demand, technostress as a potential psychological strain mechanism, turnover intention as a withdrawal-related employee outcome, and reskilling training as an organizational job resource. This conceptualization provides a consistent JD-R framework for examining both the potential strain-producing consequences of AI integration and the extent to which organizational resources may buffer these consequences.

AI and Automation Integration and Technostress

Technostress refers to psychological strain associated with difficulties in coping with, adapting to, or effectively using technologies in the workplace (Lainjo, 2021). From a JD-R perspective, AI integration may contribute to technostress when the technological demands associated with adaptation require sustained effort beyond the resources employees perceive to be available. Employees may need to continuously learn new systems, adjust to changing technological procedures, and maintain performance while simultaneously developing new digital competencies. These requirements may increase cognitive and psychological demands associated with work.

AI-integrated work environments may also expose employees to several technology-related stressors. Techno-uncertainty may arise when employees experience continuous technological changes and uncertainty concerning future work requirements (Boddu et al., 2022). Techno-overload may occur when technology increases the amount or speed of information that employees must process (Jabeen et al., 2022), while techno-insecurity may emerge when employees perceive that their existing skills could become less relevant as technological capabilities advance (Khammissa et al., 2022). These conditions do not imply that AI integration inevitably produces technostress. Rather, JD-R Theory suggests that technostress is more likely to emerge when employees experience AI-related requirements as demanding and insufficiently matched by available resources.

Accordingly, greater AI and automation integration may increase employees' exposure to technological demands that require sustained adaptation. When these demands accumulate, employees may experience greater psychological difficulty in managing their technologically transformed work environment. Based on the job demands and strain mechanism proposed by JD-R Theory, this study therefore expects a positive relationship between AI and automation integration and technostress.

H1: AI and Automation Integration has a positive effect on Technostress.

Technostress and Turnover Intention

JD-R Theory proposes that persistent job demands can initiate a health-impairment process in which sustained expenditure of cognitive and psychological effort produces strain and deteriorates employee well-being. Technostress represents one form of such strain in technologically intensive work environments. When employees repeatedly experience technological overload, uncertainty, complexity, or insecurity, maintaining effective performance may require substantial psychological effort (Psarommatidis et al., 2023; Passalacqua et al., 2022).

Persistent technostress may consequently affect employees' attitudes toward remaining in their organization. Employees who continuously expend psychological resources to cope with technological pressures may experience emotional exhaustion, reduced job satisfaction, and weaker attachment to their work environment (Arnold et al., 2023). Under such conditions, considering withdrawal from the organization may represent a behavioral response to an environment perceived as persistently demanding. Previous research has similarly associated technology-related strain with unfavorable employee attitudes and withdrawal-related outcomes (Rasool et al., 2022).

Within the JD-R framework, this reasoning suggests that technostress can transmit the consequences of excessive technological demands into a withdrawal-related outcome. As technostress increases, employees may become more inclined to consider leaving their organization to avoid continued exposure to demanding technological conditions. Therefore, the following hypothesis is proposed:

H2: Technostress has a positive effect on Turnover Intention.

AI and Automation Integration and Turnover Intention

Although technostress represents one potential psychological pathway through which employees may respond to AI integration, JD-R Theory does not require all consequences of job demands to operate through a single strain mechanism. AI integration may also be directly associated with turnover intention when employees perceive AI-driven changes as substantially altering their work requirements, roles, or ability to remain effective within the organization.

As organizations increase their reliance on AI and automation, employees may encounter changes in task structures, competency requirements, and human-machine responsibilities (Bojic, 2022). These changes may create substantial adaptation demands even when employees do not experience pronounced technostress. For example, employees may reconsider their organizational future when AI-driven restructuring changes the competencies required for their positions or creates uncertainty about the continuity and relevance of existing roles (Chilunjika et al., 2022). Thus, the decision to consider leaving may reflect employees' evaluation of changing work conditions and future role compatibility rather than solely an accumulated stress response.

From a JD-R perspective, sustained exposure to demanding work conditions can influence withdrawal-related outcomes when employees perceive that continued adaptation requires effort that is difficult to maintain. Consequently, AI integration may be positively associated with turnover intention independently of the specific technostress pathway. Testing this direct relationship is also important for determining whether technostress accounts for the relationship between AI integration and turnover intention or whether additional mechanisms may be involved.

H3: AI and Automation Integration has a positive effect on Turnover Intention.

The Mediating Role of Technostress

The JD-R health-impairment process provides the theoretical basis for proposing technostress as a mediating mechanism between AI and automation integration and turnover intention. AI integration may introduce technological job demands that require employees to continuously learn, adapt, and modify established work practices. When these demands become psychologically difficult to manage, employees may experience technostress. Persistent technostress may subsequently increase their inclination to withdraw from the demanding work environment.

This proposed mechanism distinguishes the presence of technological change from employees' psychological responses to that change. AI integration itself does not necessarily produce withdrawal intention solely because new technology is present. Rather, one theoretically plausible pathway is that AI-related demands increase technological strain, which subsequently contributes to turnover intention. This mechanism is consistent with the JD-R proposition that demanding job characteristics may influence employee outcomes through a strain-producing process.

Importantly, technostress is examined as a potential rather than predetermined mediating mechanism. Testing this mediation therefore allows the study to determine empirically whether the relationship between AI integration and turnover intention operates through technological strain or whether AI integration may influence turnover intention through other mechanisms. Based on this reasoning, the following hypothesis is proposed:

H4: Technostress mediates the relationship between AI and Automation Integration and Turnover Intention.

The Moderating Role of Reskilling Training

Reskilling training refers to structured organizational initiatives designed to equip employees with new competencies required to perform effectively in changing work roles, particularly those involving AI and automation (Zidaru et al., 2021). Within JD-R Theory, reskilling training can be conceptualized as a job resource because it provides employees with knowledge, competencies, and developmental support that may facilitate adaptation to emerging technological demands. Job resources are particularly relevant when employees encounter high job demands because they can support goal achievement and reduce the psychological costs associated with adapting to demanding work conditions (Bankins et al., 2024).

When AI integration substantially changes work processes and competency requirements, employees with access to effective reskilling opportunities may perceive themselves as better prepared to adapt to these changes. Training can improve employees' technological competence, increase their perceived capacity to work with AI-based systems, and signal organizational investment in their continued development. Consequently, the availability of reskilling training may weaken the extent to which AI-related job demands translate into intentions to leave the organization.

The moderating argument therefore does not assume that reskilling training eliminates the challenges associated with AI adoption (Bankins et al., 2024). Rather, consistent with JD-R Theory, it proposes that the availability of an organizational job resource may buffer the relationship between technological job demands and withdrawal-related outcomes. Accordingly, the positive relationship between AI integration and turnover intention is expected to be weaker when employees perceive higher levels of reskilling training.

H5: Reskilling Training moderates the relationship between AI and Automation Integration and Turnover Intention, such that the positive relationship is weaker when Reskilling Training is higher.

Reskilling training may also influence how employees respond when technological demands have already resulted in technostress. Employees experiencing technostress may perceive technological changes as difficult to manage because they lack sufficient knowledge, skills, or confidence to respond effectively. Training can provide additional resources that strengthen technological competence and improve employees' perceived ability to cope with changing work requirements (Bakker & de Vries, 2021).

From the JD-R perspective, access to these resources may buffer the translation of technological strain into withdrawal intention. Employees experiencing technostress but receiving adequate reskilling opportunities may perceive greater possibilities for adaptation within their current organization, whereas employees with limited developmental resources may be more inclined to consider leaving when exposed to comparable levels of technological strain. Thus, reskilling training is expected to weaken the positive association between technostress and turnover intention.

H6: Reskilling Training moderates the relationship between Technostress and Turnover Intention, such that the positive relationship is weaker when Reskilling Training is higher.

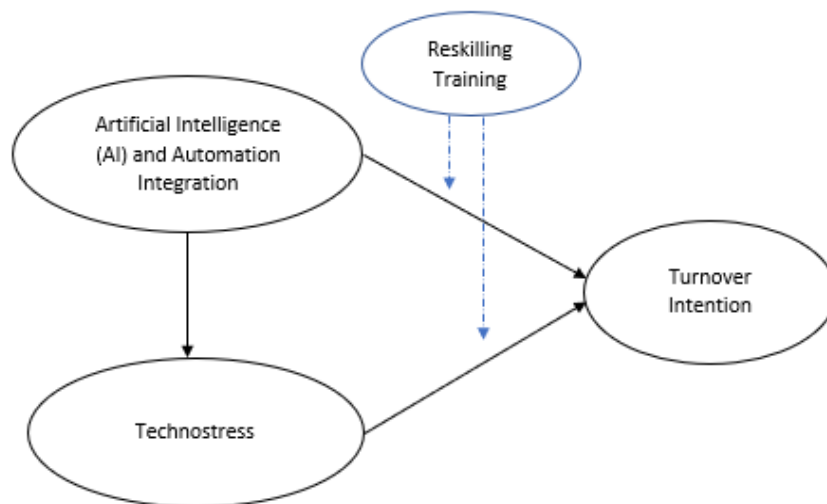


Figure 1. Conceptual Model

2. METHOD

This study employed a quantitative research approach to examine the relationships among AI and automation integration, technostress, reskilling training, and employee turnover intention. A positivist research perspective was adopted because the study aims to empirically examine hypothesized relationships among measurable constructs using statistical analysis rather than exploring subjective experiences qualitatively (Yu et al., 2022). Data collection was conducted in 2025 using a structured questionnaire distributed through Google Forms.

Before accessing the questionnaire, respondents were required to answer preliminary screening questions to ensure that they met the research criteria. Specifically, respondents were asked whether they had direct experience using AI or automation technologies within their workplace environment and whether they were willing to participate voluntarily. This screening procedure ensured that the collected responses represented employees with relevant exposure to AI-integrated work environments.

A total of 265 respondents participated in this study. The respondents were selected from employees working in AI and automation-adopting organizations in Mataram, West Nusa Tenggara (NTB). This specific context was selected because employees in these organizations have direct experience with technological transformation and can provide relevant insights into how AI adoption influences workplace attitudes and behavioral intentions.

Sampling Procedure

The study employed purposive sampling because a complete sampling frame of employees working with AI and automation technologies was unavailable. Purposive sampling was considered appropriate because the research required respondents with specific characteristics related to AI exposure rather than a general employee population.

The inclusion criteria required respondents to be employees who:

- (1) worked in organizations that had implemented AI or automation technologies,
- (2) had direct interaction with AI-based systems or automated processes in their work activities, and
- (3) were willing to provide voluntary responses.

These criteria ensured that respondents possessed sufficient knowledge and experience to evaluate the impact of AI integration, technological demands, and organizational support within their workplace context. However, because the study focuses on employees in AI-adopting organizations in Mataram, NTB, the findings should be interpreted within this specific geographical and organizational setting rather than generalized to all employees or industries.

The demographic characteristics of respondents, including gender, age, education level, technology exposure, and employment status, are presented in Table 1.

Survey Instrument

The measurement instrument was developed by adapting previously validated measurement scales from prior studies. The constructs were measured using established instruments related to AI and automation integration (Kiran, 2021), technostress (Shiau et al., 2022), reskilling training (Mezhoudi et al., 2023), and turnover intention (Namin et al., 2022). The original measurement items were adjusted to align with the context of AI-integrated workplaces while maintaining the conceptual meaning of each construct.

The questionnaire consisted of two sections. The first section collected demographic information, including gender, age, education level, technology exposure, and employment status. The second section measured respondents' perceptions and experiences regarding AI integration, technostress, reskilling training, and turnover intention. All measurement items were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). To minimize potential common method bias, the questionnaire design ensured respondent anonymity, clarified that there were no right or wrong answers, and reduced evaluation apprehension during data collection.

Sample Characteristics

The demographic profile of the respondents is shown by looking at some of the observed characteristics. The gender categories show that the male category is 84, while the female category is more numerous with 181 respondents. Age was categorized into three groups: teenagers (18-22), adults (23-32), and elders (>32). Education was divided into three categories: high school graduates, undergraduates, and post-graduates. Self-rated technology exposure level was divided into three groups: low, medium and high. Current employment status was categorized into two: part-time and full-time.

Table 1. Respondent Characteristics

Characteristic	Total
Gender	
Male	84
Female	181
Age	
18-22	17
23-32	104
>32	144
Last Education	
Senior High School / Vocational School	233
S1/D3	32
S2/S3	-
Technology Exposure Level (Self-Rated)	
Low	34
Medium	179
High	52
Employment Status	
Part-time	167
Full-time	98

Table 2. Measurement Model

Variabel	Item	Loading	AVE	Discriminant Validity	CR
Artificial Intelligence (AI) and Automation Integration	Routine Tasks Taken Over	0.747	0.615	0.747	0.889
	Reliance on AI Analytics	0.745		0.745	
	Mandatory Skill Change	0.781		0.781	
	AI as a Coworker	0.822		0.822	
	AI Erodes the Value of Expertise	0.823		0.823	
Technostress	Exhaustion	0.603	0.576	0.603	0.868
	Exhaustion	0.880		0.880	
	Sinisme	0.777		0.777	
	Sinisme	0.880		0.880	
	Lack of Effi-cacy	0.602		0.602	
Reskilling Training	Program Availability	0.623	0.525	0.623	0.846
	Relevance Konten	0.781		0.781	
	Organizational Support	0.786		0.786	
	Competency Improvement	0.742		0.742	
	Long-term Focus	0.678		0.678	
Turnover Intention	Job Seeking Intention	0.660	0.657	0.660	0.905
	Desire to Quit	0.844		0.844	
	Organization Comparison	0.844		0.844	
	Short-term Intention	0.845		0.845	
	Recommendations to Others	0.844		0.844	

Source: SmartPLS 4

Data analysis in this study used a structural equation modeling (SEM) approach with the SMART PLS Version 4 analysis tool. The analysis process consists of two main stages, namely the measurement model and structural model stages. In the first stage, construct validity and reliability were tested through the measurement of average variance extracted (AVE) and composite reliability (CR). As a standard, the AVE value must be ≥ 0.5 (Hair & Sarstedt, 2021), and the CR value must be ≥ 0.6 (Cheung et al., 2024). Although an outer loading value of 0.70 is generally recommended, indicators with loading values between 0.40 and 0.70 can still be retained when the construct meets the required AVE and CR criteria and when the indicators maintain theoretical relevance to the measured construct (Hair & Sarstedt, 2021). The analysis results show that the AVE value for each construct in this study is in the range of 0.525 to 0.657, and the CR values range from 0.846 to 0.905, indicating adequate validity and reliability. Several indicators, such as Exhaustion (0.603), Lack of Efficacy (0.602), Program Availability (0.623), Long-term Focus (0.678), and Job Seeking Intention (0.660), showed loading values below 0.70; however, these indicators were retained because the overall measurement model remained acceptable, with

AVE values above 0.50 and strong composite reliability values.

Furthermore, to test discriminant validity, we used the square root of AVE approach, where the square root of AVE value for each construct should be greater than the correlation between constructs. The analysis results show that the entire square root of AVE is greater than the correlation between constructs in the model, which confirms good discriminant validity (Dash & Paul, 2021). The discriminant validity values for all constructs met the criteria, with a range of values between 0.602 to 0.880, indicating excellent reliability. Once the measurement model met the validity and reliability requirements, we proceeded to the structural model testing phase to test the hypotheses, focusing on the direct, mediating, and moderating effects between constructs. Direct tests were conducted to measure the effect of Artificial Intelligence (AI) on Turnover Intention, while moderated tests evaluated the role of Reskilling Training in moderating the relationship between AI and Turnover Intention. This approach provides a more holistic picture of how AI and automation affect turnover intention through the role of technostress and reskilling training in technology-based workplaces.

3. RESULT AND DISCUSSION

To assess potential collinearity issues that may influence the structural relationships, a variance inflation factor (VIF) assessment was conducted using the SmartPLS 4 algorithm. The VIF values were examined for all predictor relationships in the structural model to ensure that the estimated path coefficients were not affected by excessive multicollinearity among constructs. The results of the collinearity assessment are presented in Table 3.

Table 3. Full Collinearity VIF Assessment

	Collinearity VIF
AI Integrated to Technostress	1.000
AI Integrated to Turnover Intention	2.004
Reskilling to Turnover Intention	2.152
Technostress to Turnover Intention	1.069
Reskilling x Technostress to Turnover Intention	1.357
Reskilling x AI Integrated to Turnover Intention	1.249

Source: SmartPLS 4

Table 3 indicate that all VIF values in the structural model were below the recommended threshold of 5.00, suggesting that multicollinearity was not a critical concern among the predictor constructs. The highest VIF value was observed for the relationship between Reskilling Training and Turnover Intention ($VIF = 2.152$), which remains within the acceptable range. These findings indicate that the structural relationships among AI Integration, Technostress, Reskilling Training, and Turnover Intention were not substantially affected by collinearity problems. Therefore, the estimated path coefficients can be interpreted with confidence in the subsequent structural model analysis. The results of the effect size assessment are presented in Table 4.

Table 4. F square

	f²	Description
AI Integrated to Technostress	0.200	Medium Effect
AI Integrated to Turnover Intention	4.108	Large Effect
Reskilling to Turnover Intention	0.720	Large Effect
Technostress to Turnover Intention	0.250	Medium Effect
Reskilling x Technostress to Turnover Intention	0.500	Large Effect
Reskilling x AI Integrated to Turnover Intention	0.800	Large Effect

Source: SmartPLS 4

Table 4 show that the effect sizes of the structural relationships vary across constructs. AI Integration → Technostress demonstrates a medium effect ($f^2 = 0.200$), indicating that AI integration contributes meaningfully to explaining variations in technostress. AI Integration → Turnover Intention shows a large effect ($f^2 = 4.108$), while Reskilling Training → Turnover Intention also demonstrates a large effect ($f^2 = 0.720$). Furthermore, Technostress → Turnover Intention shows a medium effect ($f^2 = 0.250$). The interaction effects of Reskilling Training on the relationships between AI Integration and Technostress with Turnover Intention also demonstrate large effect sizes. These findings indicate that the predictor constructs provide meaningful contributions to explaining employee turnover intention within AI-integrated workplaces. The results of the R^2 assessment are presented in Table 5.

Table 5. R square

	R2	R2Adjusted
Technostress	0.059	0.056
Turnover Intention	0.873	0.870

Source: SmartPLS 4

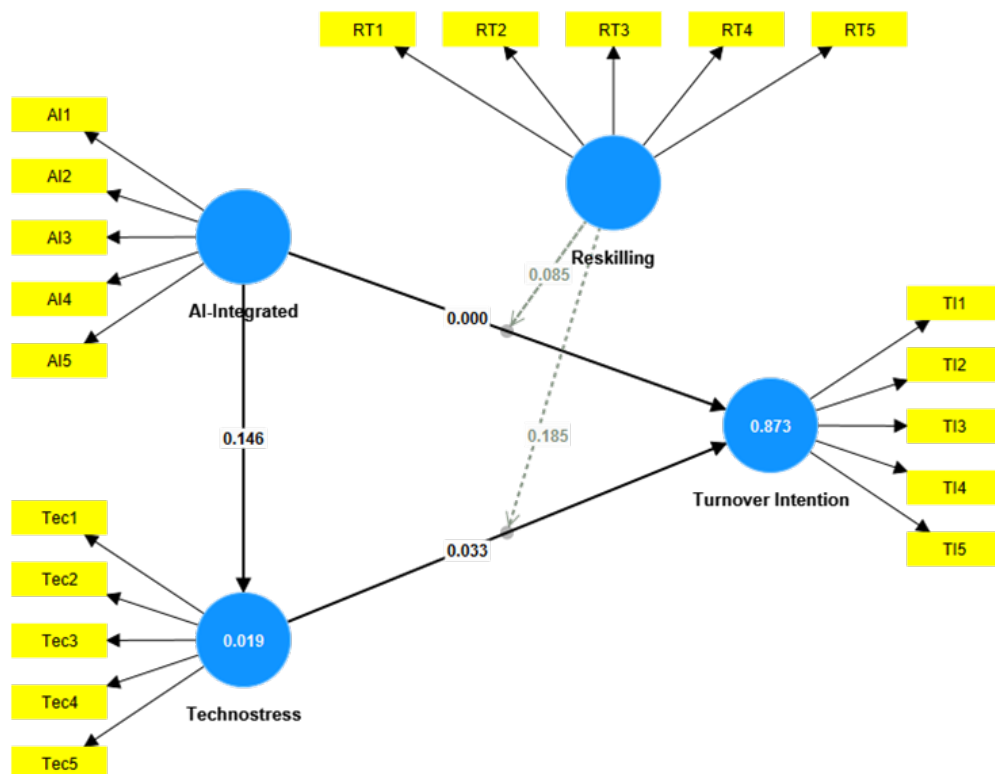
Table 5 indicate that AI Integration explains 5.9% of the variance in Technostress ($R^2 = 0.059$), suggesting a weak explanatory power for this construct. Meanwhile, AI Integration, Technostress, Reskilling Training, and the interaction effects explain 87.3% of the variance in Turnover Intention ($R^2 = 0.873$), indicating substantial explanatory power. These findings suggest that the proposed model provides a strong explanation of employees' turnover intention in AI-integrated workplaces, although the contribution of AI integration alone in explaining technostress remains limited. The results of the model fit assessment are presented in Table 6.

Table 6. Fit Model

	Estimated Model	Parameter	Description
SRMR	0.065	< 0,10	Fit
NFI	0.947	>0,90	Fit

Source: SmartPLS 4

Table 6 indicate that the structural model demonstrates an acceptable model fit. The SRMR value of 0.065 is below the recommended threshold of 0.10, indicating a satisfactory difference between the observed and predicted correlations. Furthermore, the NFI value of 0.947 exceeds the recommended threshold of 0.90, suggesting an adequate fit between the proposed model and the observed data. Therefore, the structural model can be considered appropriate for subsequent hypothesis testing and interpretation.

**Figure 2. Bootstrapping Results**

The proposed research model was evaluated using a structural equation modeling (SEM) approach with SmartPLS Version 4. The data used in this study were obtained from 265 respondents. The results of direct hypothesis testing are presented in Table 7, which illustrates the estimated relationships between constructs without considering moderating effects. The structural model was evaluated based on path coefficients, T-

statistics, and P-values obtained through the bootstrapping procedure.

The first finding shows that AI and Automation Integration has a positive effect on Technostress, with a path coefficient of $\beta = 0.139$, but the relationship is statistically insignificant (T-statistics = 1.053; P-value = 0.146 > 0.05). Therefore, H1, which proposed that AI and Automation Integration has a positive and significant effect on Technostress, was not supported. Although the positive coefficient indicates that greater AI integration is associated with higher technostress, the empirical evidence does not confirm that AI integration significantly increases employees' technological strain in this research context. This finding suggests that AI adoption does not necessarily produce immediate psychological strain among employees (Henderson & Corry, 2021). From the perspective of JD-R Theory, although AI integration can be considered a potential technological job demand, its impact on employee strain may depend on whether employees perceive sufficient resources to cope with these demands. One possible explanation is that employees may perceive AI-based systems as supportive tools that assist work processes rather than as additional burdens. Therefore, the presence of AI technology alone may not be sufficient to generate significant technostress without considering other contextual factors, such as organizational support, employee readiness, or the nature of technology implementation.

The second finding indicates that Technostress has a positive and significant effect on Turnover Intention, with $\beta = 0.059$, T-statistics = 1.835, and P-value = 0.033 < 0.05. Therefore, H2, which proposed that Technostress has a positive and significant effect on Turnover Intention, was supported. The positive coefficient indicates that employees experiencing higher levels of technostress tend to demonstrate stronger intentions to leave their organizations. This finding supports the JD-R theoretical perspective, which suggests that persistent job demands may generate psychological strain that influences employee outcomes. In technologically intensive workplaces, technostress may represent a strain response arising from difficulties in adapting to technological requirements, which can subsequently weaken employees' willingness to remain within the organization. Employees experiencing technological difficulties may perceive their work environment as increasingly demanding, which can contribute to withdrawal-related intentions (Pressley & Garside, 2023).

The third finding indicates that AI and Automation Integration has a positive and statistically significant relationship with Turnover Intention, with $\beta = 1.024$, T-statistics = 31.467, and P-value = 0.000 < 0.05. Therefore, H3, which proposed that AI and Automation Integration has a positive and significant effect on Turnover Intention, was initially supported. However, this finding was interpreted cautiously because the estimated path coefficient exceeded the conventional standardized range expected in PLS-SEM. To address this concern, additional structural model evaluations were conducted, including collinearity assessment, effect size analysis, explanatory power evaluation, and model fit assessment. The results indicated that the structural model did not present critical collinearity problems, and the relationship was therefore retained for further interpretation.

From the perspective of JD-R Theory, this finding suggests that AI integration may represent a technological job demand that influences employee turnover intention through broader workplace transformation mechanisms beyond psychological strain alone. Employees may evaluate AI-driven changes based on perceived changes in job roles, future career compatibility, skill requirements, and organizational adaptation processes. Thus, the relationship between AI integration and turnover intention should not be interpreted as an inevitable negative consequence of AI adoption, but rather as an outcome shaped by how employees perceive and experience AI-related workplace changes. This interpretation is consistent with previous studies highlighting that rapid technological transformation can influence employees' perceptions of future work conditions and organizational attachment (Liu-Lastres et al., 2023; Liu-Lastres et al., 2024).

Table 7. Structural Model

Path Coefficient	Original Sample	T statistics	P values	Decision
AI-Integrated to Technostress	0.139	1.053	0.146	Not Supported
AI-Integrated to Turnover Intention	1.024	31.467	0.000	Supported
Technostress to Turnover Intention	0.059	1.835	0.033	Supported

Source: SmartPLS 4

The mediation analysis examined whether Technostress explains the relationship between AI and Automation Integration and Turnover Intention. The results indicate that Technostress does not significantly mediate this relationship, with an indirect effect coefficient of $\beta = 0.008$, T-statistics = 1.204, and P-value = 0.114. Therefore, H4, which proposed that Technostress mediates the relationship between AI and Automation Integration and Turnover Intention, was not supported. This finding suggests that although AI integration is significantly associated with turnover intention, the relationship is not primarily explained through technological strain in the form of technostress within this research context. From the perspective of JD-R Theory, the proposed

strain pathway in which AI integration functions as a technological job demand that generates technostress and subsequently increases turnover intention was not empirically confirmed.

However, this finding does not indicate that technostress is irrelevant, as technostress remains significantly associated with turnover intention in the direct relationship. Instead, the result suggests that employees' responses to AI integration may involve broader mechanisms beyond technological strain alone. This finding differs from previous studies suggesting that technostress can mediate the relationship between technology-related changes and employee outcomes (Hauk et al., 2019). The results therefore highlight that AI-driven workplace transformation may influence turnover intention through multiple pathways, and technostress may not represent the dominant mechanism in this specific organizational context.

Table 8. Mediation

Path Coefficient	Original Sample	T statistics	P values	Decision
AI-Integrated -> Technostress -> Turnover Intention	0.008	1.204	0.114	Not Supported

Source: SmartPLS 4

Furthermore, the moderating effects of Reskilling Training were examined to determine whether it changes the relationships between AI Integration and Turnover Intention, as well as between Technostress and Turnover Intention. The first finding related to hypothesis H5 indicates that Reskilling Training does not significantly moderate the relationship between AI Integration and Turnover Intention. The interaction effect between Reskilling Training and AI Integration produced a path coefficient of 0.026, T-statistics of 1.374, and P-value of 0.085, which exceeds the 0.05 significance threshold. Therefore, H5 was not supported. Although the interaction coefficient indicates a positive direction, the effect was not statistically sufficient to demonstrate that reskilling training changes the relationship between AI integration and turnover intention. From the perspective of JD-R Theory, this finding suggests that although reskilling training represents an important job resource, its availability alone may not be sufficient to significantly buffer the potential effects of AI-related workplace demands on employees' turnover intentions.

The second finding related to hypothesis H6 shows that Reskilling Training also does not significantly moderate the relationship between Technostress and Turnover Intention. The interaction effect between Reskilling Training and Technostress produced a path coefficient of 0.022, T-statistics of 0.898, and P-value of 0.185, indicating that the moderating effect was not statistically significant. Therefore, H6 was not supported. This finding indicates that while reskilling training may provide employees with additional knowledge and technical capabilities, it was not empirically confirmed as a factor that weakens the relationship between technostress and turnover intention in this study context.

Overall, the results indicate that Reskilling Training did not function as a significant buffering resource in the proposed relationships. This does not imply that reskilling training is ineffective, but rather suggests that skill development alone may not be sufficient to influence employees' responses toward AI-driven workplace changes. Consistent with JD-R Theory, organizational resources may need to extend beyond training programs and include broader forms of support that help employees manage technological demands and adapt to workplace transformation.

Table 9. Moderation

Path Coefficient	Original sample	T statistics	P values	Decision
Reskilling x AI-Integrated -> Turnover Intention	0.026	1.374	0.085	Not Supported
Reskilling x Technostress -> Turnover Intention	0.022	0.898	0.185	Not Supported

Source: SmartPLS 4

Finally, this study examined the moderating role of Reskilling Training in the relationships between AI Integration and Turnover Intention, as well as between Technostress and Turnover Intention. The results indicate that Reskilling Training did not significantly moderate either relationship. Although reskilling training may enhance employees' technical capabilities and readiness to interact with new technologies, the findings suggest that it did not significantly alter the relationship between AI integration and turnover intention or between technostress and turnover intention in this research context. From the perspective of JD-R Theory, this finding suggests that while reskilling training represents an important job resource, its buffering effect may depend on the availability of other organizational resources and contextual conditions that support employees during technological transformation. Therefore, reskilling training should not be interpreted as ineffective; rather, its role as a moderating resource was not empirically confirmed within the proposed model.

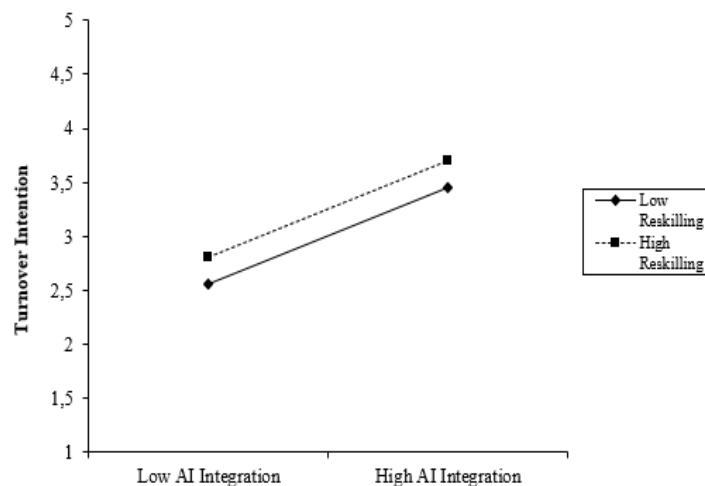


Figure 3. Plot Area Variabel AI Integration

Following Dawson F (2014) approach for interpreting interaction effects, the interaction graph visually supports the statistical finding that Reskilling Training does not significantly moderate the positive relationship between AI Integration and Turnover Intention. The lines representing the Low Reskilling and High Reskilling groups show similar slopes across different levels of AI Integration, indicating that the strength of the relationship between AI Integration and Turnover Intention remains relatively consistent regardless of employees' level of reskilling training. Although the High Reskilling group displays a slightly different level of turnover intention compared with the Low Reskilling group, the absence of a substantial difference in slope indicates that reskilling training does not significantly change the effect of AI integration on turnover intention. This graphical pattern is consistent with the statistical result showing that the interaction effect was not significant.

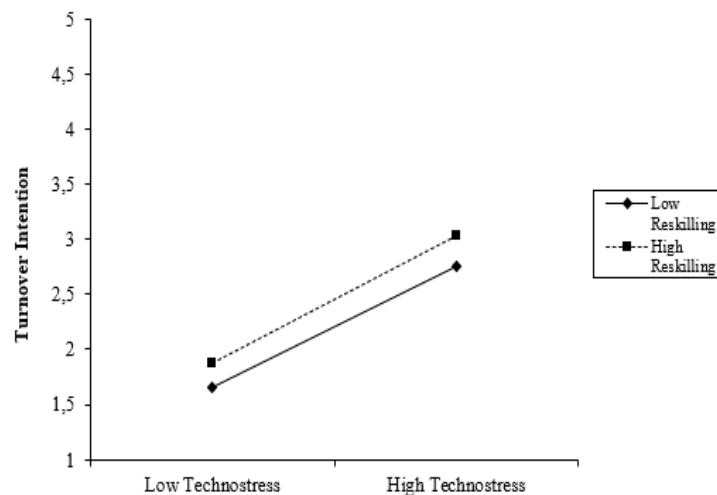


Figure 4. Plot Area Variabel Technostress

Following the interaction plot interpretation procedure suggested by Dawson F (2014), the interaction graph visually supports the conclusion that Reskilling Training does not moderate the positive relationship between Technostress and Turnover Intention. The Low Reskilling and High Reskilling lines show relatively similar slopes, indicating that the relationship between Technostress and Turnover Intention remains consistent across different levels of training. Although the High Reskilling group shows a slightly different level of Turnover Intention, the absence of a significant difference in slope confirms that Reskilling Training does not significantly change the effect of Technostress on employees' turnover intention.

The results of this study provide a deeper understanding of the relationship between AI Integration, Technostress, and Turnover Intention in an increasingly digitized workplace. Based on the Job Demands-

Resources (JD-R) Theory, AI Integration can be considered a potential technological job demand, while Reskilling Training represents a job resource that may help employees manage technological changes (Bakker & de Vries, 2021). However, the findings suggest that employee responses toward AI adoption are more complex than a simple demand-strain process.

The first finding shows that although AI and Automation Integration has a positive relationship with Technostress, the effect is not statistically significant. This indicates that AI integration does not automatically generate technological strain among employees in this research context. Employees may perceive AI as a supportive tool that assists work processes rather than as an additional burden. Within JD-R Theory, this finding suggests that technological demands may not always produce strain when employees perceive sufficient resources or adaptability in dealing with technological changes.

Technostress has a significant positive influence on Turnover Intention. The higher the level of Technostress experienced by employees, the greater their intention to leave the organization. This finding supports the JD-R perspective that excessive job demands can generate strain and influence withdrawal-related outcomes. Employees experiencing difficulties in managing technological requirements may develop stronger intentions to seek alternative work environments (Pressley & Garside, 2023).

AI and Automation Integration also has a significant positive influence on Turnover Intention. This finding suggests that AI adoption may influence employees' decisions to remain or leave the organization beyond the effect explained by technostress. From the JD-R perspective, AI integration may represent a substantial technological demand that influences employee attitudes when organizational resources are perceived as insufficient. However, the specific psychological mechanisms underlying this relationship require further investigation.

Although AI Integration and Technostress both show significant relationships with Turnover Intention, Technostress does not significantly mediate the relationship between AI Integration and Turnover Intention. This indicates that the direct relationship between AI integration and turnover intention is not primarily explained through technostress in this research context. Within JD-R Theory, the strain pathway proposed in this study was not empirically supported, suggesting that other mechanisms may contribute to employees' responses toward AI-driven workplace transformation.

The moderation analysis also shows that Reskilling Training does not significantly influence the relationships between AI Integration and Turnover Intention or between Technostress and Turnover Intention. Although reskilling training can provide employees with valuable skills and represents an important job resource, its buffering effect was not statistically confirmed in this study. This suggests that skill development alone may not be sufficient to alter employees' responses toward AI-related workplace demands.

Overall, the findings indicate that Reskilling Training should not be interpreted as ineffective, but rather that its role as a moderating resource may depend on broader organizational conditions and additional forms of support. In the context of JD-R Theory, addressing technological challenges may require a combination of resources, including training, communication, and organizational support, rather than relying on training programs alone.

The findings of this study contribute to the AI and employee management literature by showing that AI integration does not necessarily increase technostress, even though it is associated with turnover intention. Furthermore, the absence of significant mediation and moderation effects highlights that employee responses toward AI transformation may involve multiple pathways beyond technological strain and reskilling resources.

From a practical perspective, organizations should not only focus on providing technical training but also develop broader strategies to support employees during AI transformation. Managers and HR practitioners should combine reskilling initiatives with effective communication, role clarification, and continuous organizational support to help employees adapt to AI-integrated workplaces. These approaches may provide a more comprehensive response to employee concerns regarding technological change.

4. CONCLUSION

This study aims to analyze the relationship between AI Integration and Turnover Intention while examining the mediating role of Technostress and the moderating role of Reskilling Training in an AI-integrated workplace context. The findings indicate that AI Integration has a significant positive relationship with Turnover Intention, suggesting that AI-driven workplace transformation may influence employees' intention to leave their organizations. However, Technostress did not significantly mediate this relationship, indicating that the influence of AI integration on turnover intention may not primarily operate through technological strain. Although Technostress was found to have a significant positive relationship with Turnover Intention, the proposed mediation mechanism was not supported. Similarly, Reskilling Training did not significantly moderate the relationships between AI Integration and Turnover Intention or between Technostress and Turnover Intention. These findings suggest that while reskilling training represents an important job resource, its buffering effect may depend on

broader organizational conditions and additional forms of support beyond skill development alone. Based on the Job Demands-Resources (JD-R) Theory, this study contributes by showing that AI Integration may function as a technological job demand that influences employee withdrawal intentions, while the psychological pathway through Technostress and the buffering role of Reskilling Training may not always be dominant. Therefore, organizations should adopt comprehensive strategies, including effective communication, organizational support, and employee development initiatives, to manage AI-related workplace changes. Future research is encouraged to explore other contextual factors, such as leadership, organizational support, and employee adaptability, that may further explain how AI integration influences employee turnover intention.

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