Journal of STI Policy and Management, Volume 10(2), 2025, pp. 31-48

STI POLICY AND MANAGEMENT

Journal homepage: http://www.stipmjournal.org

Balancing AI's Promise and Pressure: A Dual Process Model of AI Adoption, Psychological States, and Employee Performance in Indonesia

Asmini*

Management Department, Universitas Lamappapoleonro, Soppeng, South Sulawesi, Indonesia

ARTICLE INFO

Article History:
Received : 24 July 2025
Revised : 5 November 2025
Accepted : 6 December 2025
Available online : 15 December 2025

Authorship Contribution:
Asmini is the main author

Keywords:
AI Adoption;
Employee Performance;
Indonesia;
Psychological Mechanisms;
Digital Transformation.

ABSTRACT

This research aims to explore how AI adoption impacts employee performance via the dual process between competing psychological mechanism: a positive path through technological self efficacy and job engagement, and a negative path through perceived job insecurity and AI induced stress. The proposed relationships are investigated through structural equation modeling with SmartPLS and data collected from 280 Indonesian employees working in diverse business sectors. They also confirm the dual process view stating that employment of AI actually improves the performance by promoting user engagement and trust. However, the results also demonstrate that AI use can result in psychological stress and job uncertainty, both of which negatively impact employee performance. The coexistence of opportunity and risk in AI-driven transformation is highlighted by the statistical significance of both positive and negative sequential mediations. These findings contribute to theory by integrating the perspectives of emotional threat and cognitive motivation into a single framework. Practically speaking, the study emphasises the significance of organisational initiatives that both reduce anxiety and emotional strain related to technology disruption and empower workers through the development of digital skills. The results are especially pertinent to developing nations such as Indonesia, where labour preparedness and institutional safeguards may not always keep up with the rapid diffusion of AI.

* Corresponding Author.
E-mail: asmini@unipol.ac.id

DOI: 10.14203/STIPM.2025.429

I. INTRODUCTION

The quick adoption of artificial intelligence (AI) in the workplace has completely changed how workers complete tasks, make choices, and communicate with digital systems (Zirar et al., 2023). This transition is a reflection of what Schwab (2017) refers to as the Fourth Industrial Revolution, a time when physical, biological, and digital systems come together to produce technological change of previously unheard of complexity, speed, and scope. AI is not merely an automation tool in this transformation; it is a catalyst that is changing human potential, organisational culture, and the structure of labour. AI is being adopted at an increasingly rapid pace across numerous industries in Indonesia, including manufacturing, healthcare, education, finance, and hospitality, where it facilitates automation, analytics, and customer assistance (Yuniawan et al., 2025). As both government and private enterprises advance digital transformation agendas aligned with the national Making Indonesia 4.0 roadmap. AI is no longer a distant innovation but a central component of daily work life. AI creates new psychological demands, demanding workers to constantly adapt, learn, and rearrange their professional positions in a dynamic digital economy, even as it promises increased productivity and operational efficiency (Khan et al., 2025; Muhammad et al., 2025).

Prior research has primarily emphasized the positive dimensions of AI adoption, including improved decision making, task efficiency, and job enrichment (Castaneda et al., 2026; Jerez-Jerez, 2025; Song et al., 2025). In Indonesia, AI is often portrayed as a strategic instrument that empowers workers and enhances organizational performance, particularly in firms embracing Industry 4.0 technologies (Fitriani and Basir, 2025; Jamaluddin, 2025). Nevertheless, as Schwab (2017) cautions, technological revolutions that redefine production and interaction systems also disrupt established social and occupational structures. Similarly, recent research shows that not all employees have great experiences using AI at work. Because of its quick automation and low level of digital literacy, AI may pose a threat to some workers, especially in developing nations, increasing job insecurity and technological stress (Kim and Kim, 2024). This duality positions AI as a double-edged sword: while it can stimulate learning and motivation, it may also trigger anxiety, uncertainty, and strain.

The current study uses a dual process framework to explain how employee performance is impacted by AI adoption via two opposing psychological pathways in order to resolve this conflict. AI's empowering potential is captured by the first pathway, which is based on the Job Demands Resources (JDR) paradigm. Employees who view AI as a resource that improves their competence and engagement typically perform better at work (Chuang et al., 2025). The second pathway, informed by Conservation of Resources (COR) theory, reflects AI's strain-inducing potential, as employees who perceive AI as a threat to job stability may experience heightened stress and diminished performance (Majrashi, 2025). These dual mechanisms are especially salient in Indonesia, where rapid technological change often outpaces formal upskilling initiatives and institutional protections for workers remain uneven.

Indonesia constitutes a theoretically distinctive context in which to investigates these dynamics. Its archipelagic geography creates persistent digital divides between urban and rural regions, while its large informal sector limits structured access to training and job security (Supiandi, 2024). Additionally, the National Artificial Intelligence Strategy 2045 places a high priority on technological competitiveness while giving workers' psychosocial preparation little consideration (Maria and Riswadi, 2024), exposing a disconnect between human adaptation and innovation. By placing this investigation inside Schwab's (2017) conceptualisation of the Fourth Industrial Revolution, it becomes clear that Indonesia's AI revolution is a part of a worldwide structural shift in which labour resilience and social inclusion are crucial to the advantages of automation. Investigating Indonesian workers' psychological reactions to AI adoption so advances knowledge of how socio-technical changes take place in developing nations.

This study expands on previous research on AI and human resource management by combining the JD-R and COR frameworks into a single model, showing that stress and empowerment may coexist in the same workforce. By connecting technological adoption to psychological adaptation, the analysis not only advances theory but also offers useful advice for businesses looking to use AI responsibly. The study demonstrates through empirical data from Indonesia's various industries that AI-enabled transformations can only produce long-term performance gains when businesses make concurrent investments in digital competency, employee welfare, and institutional support systems.

II. ANALYTICAL FRAMEWORK

A. Conceptualizing Artificial Intelligence (AI) Adoption in the Workplace

Employee perceptions, acceptance, and use of intelligent technologies that automate, anticipate, or enhance decision-making processes are referred to as artificial intelligence (AI) adoption in organisational settings (Mufaddhal, 2025; Ulum, 2025). AI in the workplace refers to a wide range of technologies, such as machine learning algorithms, natural language processing, and predictive analytics, which together change how tasks are carried out, information is processed, and human-digital agent interactions take place (Dwivedi et al., 2021). From a behavioural standpoint, the adoption of AI encompasses more than just the use of technology; it also represents how people absorb, adjust to, and gain significance from their interactions with these systems (Yang et al., 2024). Therefore, employees' perceptions of AI are central to understanding its broader organizational and psychological impacts.

Adoption of AI has changed workflow integration, traditional task hierarchies, and decision-making autonomy at the organisational level. Research demonstrates that by automating repetitive tasks, AI systems can increase productivity, speed up data-driven decision-making, and optimise task allocation (Ali et al., 2024; Kassa and Worku, 2025). But these same systems frequently disperse authority and influence, forcing workers to cooperate with computational tools that could change current power dynamics and professional boundaries (Maria and Riswadi, 2024). As AI permeates every aspect of corporate operations, from customer analytics to human resource management, it redefines job responsibilities and capabilities, opening up new avenues for skill development while also bringing uncertainty and cognitive demands (Jaiswal et al., 2022).

The Indonesian setting offers a unique setting for analysing these changes. The government's commitment to using AI for industrial upgrading and digital competitiveness is demonstrated by national projects like Making Indonesia 4.0 and the Artificial Intelligence Strategy 2045 (Maria and Riswadi, 2024). However, due to Indonesia's archipelagic location, there are significant regional differences in access to digital training and technological infrastructure, which leads to an unequal distribution of AI preparedness (Maria and Riswadi, 2024). The fragmented nature of technology dissemination is highlighted by the coexistence of modern urban industries and informal rural sectors, where workers in various regions have radically varying exposure and capacity levels. The difficulties of workforce adaptation are exacerbated by the lack of institutional channels for reskilling and job protection, which makes employees' subjective reactions to AI particularly significant for productivity and wellbeing (Ekuma, 2024).

Within this heterogeneous setting, AI adoption emerges as a complex socio-technical phenomenon that embodies both opportunity and risk (Ekuma, 2024). On one hand, AI can serve as a job resource that facilitates efficiency, learning, and engagement, consistent with the motivational perspective of the Job Demands Resources model (Maria and Riswadi, 2024). On the other hand, it may also function as a job demand that induces feelings of insecurity, cognitive overload, and technostress, reflecting the strain mechanisms posited by Conservation of Resources theory (Jamaluddin, 2025). These conflicting perspectives imply that the adoption of AI follows two psychological paths, empowerment and strain that can occur in the same workplace. The current work suggests a dual route model that incorporates both resource gain and resource loss views in order to resolve this issue.

B. Theoretical Foundation for the Dual Process Framework

The dual process framework in this study is anchored in four interrelated theoretical perspectives that explain how AI adoption simultaneously enables and constrains employee performance: the Job Demands–Resources (JD–R) model, Social Cognitive Theory (SCT), Conservation of Resources (COR) theory, and Technostress theory. Together, these perspectives capture the coexistence of resource-gain and resource-loss dynamics that arise as employees interact with AI systems in the workplace.

The Job Demands Resources (JDR) model provides the motivational foundation for understanding how AI can function as both a job resource and a job demand (Chuang et al., 2025). According to this concept, job demands are circumstances that call for constant effort and could cause stress, while job resources are elements of work that promote learning, development, and autonomy (Chuang et al., 2025). When workers view AI technologies as tools that increase professional capabilities and simplify jobs, they improve productivity, accuracy, and autonomy. For example, intelligent analytics and automated decision support systems can lessen workload and free up staff to concentrate on higher order cognitive tasks (Rožman et al., 2023). On the other hand, the same technologies become job demands that increase weariness and anxiety when they increase complexity, speed up performance standards, or decrease discretion (Chen et al., 2025). Therefore, the JDR model suggests that the relative balance between perceived resources and demands in an employee's work environment determines the motivational effects of AI adoption.

In addition, Social Cognitive Theory (SCT) describes how exposure to AI affects motivation and performance. According to Graham (2022), self-efficacy is the conviction that one can plan and carry out the necessary activities to deal with future circumstances. Technological self-efficacy in AI-enabled workplaces is a measure of workers' confidence in their capacity to acquire, comprehend, and use intelligent systems successfully (Medici et al., 2023). Employees are more inclined to participate proactively, stick with learning, and find joy in technologically mediated jobs when they believe they can communicate with AI. According to recent studies, self-efficacy improves job engagement and performance in the context of digital transformation in addition to facilitating technology acceptance (Nguyen, 2025; Wibowo et al., 2024). According to this perspective, self-efficacy serves as a motivating link between the adoption of AI and successful work outcomes.

The Conservation of Resources (COR) hypothesis sheds light on AI's propensity to cause strain, while JDR and SCT clarify its enabling aspects. According to COR theory, people work hard to acquire, hold onto, and safeguard important resources like emotional stability, competence, and job security. When these resources are lost or jeopardised, people get stressed (Demerouti, 2025). Employees may interpret the deployment of intelligent technologies as an indication of impending obsolescence or redundancy in the context of AI adoption. A potential loss of resources that compromises psychological security and sets off defensive coping mechanisms is the dread of being replaced by automation or excluded due to algorithmic determinations. Reduced motivation and poor performance might result from this loss spiral, especially if there are few chances for retraining or organisational support (Papagiannidis et al., 2023). Therefore, COR theory emphasises that the adoption of AI is a psychological phenomenon that might undermine perceived stability and self-worth in addition to being a technical process.

Technostress theory further explicates the emotional and affective dimensions of resource loss (Tarafdar et al., 2019).Technology-related stress has historically been associated with issues like information overload, system complexity, or continuous connectivity. AI-induced stress, on the other hand, results from deeper sources of uncertainty, such as autonomous system behaviour, opaque algorithmic judgements, and the perception that intelligent tools are monitoring performance (Issa et al., 2024; Zhang et al., 2025). Because they undermine workers' feeling of agency and control, these stressors are qualitatively different from those connected to traditional information systems. There is a constant need for cognitive adaptation due to the unpredictability of AI outputs and the quick evolution of its functions (Sidorkin, 2025). According to the COR paradigm, this type of technostress is the emotional expression of resource loss, resulting in psychological strain from perceived threats to competence and stability.

When taken as a whole, these four viewpoints provide a logical theoretical basis for the dual process framework that directs this investigation. The resource-gain process, in which the adoption of AI improves self-efficacy, engagement, and eventually performance, is captured by the JDR and SCT perspectives. The resource-loss pathway, on the other hand, is captured by the COR and Technostress views, which show how the adoption of AI causes performance deterioration, stress, and job instability. By combining these concepts, the current study conceptualises the adoption of AI as a paradoxical organisational force that both empowers and unnerves workers. It then aims to empirically investigate how these conflicting mechanisms manifest in Indonesia's quickly digitising workplace.

C. Empowering Pathway: The Gain-Oriented Process

The empowering pathway, which is based on the workplace Demands–Resources (JD–R) model and Social Cognitive Theory (SCT), describes how the adoption of AI might improve workers' performance and motivation by fostering technological self-efficacy and workplace engagement. AI systems function as employment resources that increase autonomy, competence, and learning possibilities when workers perceive them as helpful rather than dangerous (Zhang et al., 2025). Employees are encouraged to explore, learn new abilities, and boost their confidence in their digital competence when they are exposed to intelligent technologies that streamline activities or offer decision-support feedback (Rožman et al., 2023). The idea that one can control and profit from technological progress is reinforced over time by this process, which fosters a sense of competence in handling AI-mediated labour. Adoption of AI is therefore anticipated to have a favourable impact on technological self-efficacy.

H1: AI adoption positively influences technological self-efficacy.

AI systems can improve job engagement by improving work design and enabling more meaningful and effective task execution, in addition to boosting self-efficacy. According to the JD-R framework, employees are more motivated, committed, and absorbed in their job when technology offers sufficient resources including real-time feedback, process clarity, and cognitive support (Medici et al., 2023). Automation increases intrinsic motivation and engagement in AI-enabled environments by reducing repetitive task and freeing up employees to concentrate on strategic or creative aspects of their jobs (Jamaluddin, 2025).

H2: AI adoption positively influences job engagement.

The importance of efficacy beliefs in maintaining engagement is further explained by social cognitive theory. Workers that have a high level of technological self-efficacy approach AI-based work with interest and perseverance, viewing obstacles as chances to improve rather than as dangers (Bandura, 1997; Schaufeli et al., 2002). Such self-assurance fosters proactive and focused work behaviour, which helps internalise organisational objectives and fosters affective commitment.

H3: Technological self-efficacy positively influences job engagement.

Employee performance is also directly impacted by technological self-efficacy. People who believe they are capable of using AI systems are more likely to make use of cutting-edge digital features, quickly adjust to new procedures, and produce better results (Medici et al., 2023). Self-efficacy is regularly linked in empirical research to enhanced problem-solving, inventiveness, and perseverance in challenging situations (Bandura, 1997; Hou and Fan, 2024; Kim and Kim, 2024).

H4: Technological self-efficacy positively influences employee performance.

Additionally, motivated workers typically perform better due to increased vigour, focus, and commitment (Hou and Fan, 2024). By directing psychological resources towards task completion, engagement converts motivating moods into observable behavioural results (Zhang et al., 2025). Engaged workers in AI-supported work systems demonstrate adaptive collaboration with algorithmic tools in addition to making effective use of technology (Przegalinska et al., 2025).

H5: Job engagement positively influences employee performance.

By combining these connections, the empowering route proposes a sequential cognitive-motivational process whereby the adoption of AI increases technological self-efficacy, which in turn promotes job engagement and results in better performance (Liu and Mei, 2026). This developmental sequence demonstrates how perceptions of competence produce motivational energy that leads to behavioural excellence. It is consistent with the cognitive, motivational, and behavioural reasons embedded with both SCT and JDR frameworks.

H6: The relationship between AI adoption and employee performance is serially mediated by technological self-efficacy and job engagement.

D. Strain Pathway: The Loss-Oriented Process

Based on the theories of technostress and conservation of resources (COR), the strain pathway describes the negative psychological effects of AI adoption. This viewpoint highlights how AI can function as a stressor that drains psychological resources, causes insecurity, and impairs performance, in contrast to the empowering approach, which sees AI as a source of motivational gain. According to COR theory, people work hard to safeguard important resources like job security, self-efficacy, and emotional balance, and they become stressed when these resources are endangered or lost (Demerouti, 2025). In the context of AI adoption, employees often interpret technological change as a signal of potential role redundancy or reduced human relevance, triggering anxiety about future job continuity (Umair et al., 2023). A cognitive assessment of threat that undermines security and confidence in one's career prospects is represented by this dread of skill obsolescence and replacement. Workers who feel they have little control over technical changes are especially vulnerable as automation spreads throughout industries.

H7: AI adoption positively influences perceived job insecurity.

Adoption of AI can cause direct psychological stress in addition to its indirect impacts on insecurity. In contrast to traditional information systems, artificial intelligence (AI) uses adaptive algorithms, which often have opaque, dynamic, and unpredictable decision-making processes. Workers who use these systems may feel overwhelmed, confused, or lose their agency, especially if AI results have an impact on task delegation or evaluation (Umair et al., 2023). The unpredictability of intelligent tools and the necessity for continuous cognitive adjustment intensify strain responses even in technologically literate employees (Valtonen et al., 2025). Consequently, the presence of AI in daily work routines can generate stress independently of formal job insecurity.

H8: AI adoption positively influences AI-induced stress.

Perceived job insecurity further amplifies these emotional responses. When employees sense that their employment stability or skill relevance is threatened, they invest substantial cognitive and emotional effort in managing uncertainty, leaving fewer psychological resources for adaptive coping (Achnak and Vantilborgh, 2021). This dynamic aligns with COR's notion of a loss spiral, where resource depletion accelerates further loss (Demerouti, 2025). Job insecurity thereby functions as a precursor to AI-induced stress, as apprehensions about redundancy heighten sensitivity to technological pressures.

H9: Perceived job insecurity positively influences AI-induced stress.

These cognitive and affective strains have tangible behavioral consequences. Employees preoccupied with job insecurity often engage in cognitive withdrawal and display reduced discretionary effort (Agina et al., 2023). Instead of focusing on creative problem-solving or proactive engagement, they adopt self-protective behaviors aimed at conserving remaining resources (Demerouti, 2025). This defensive posture undermines task performance and weakens commitment to organizational goals.

H10: Perceived job insecurity negatively influences employee performance.

Similarly, AI-induced stress exerts a direct negative impact on performance outcomes. Heightened stress interferes with concentration, reduces creativity, and impairs working memory, thereby constraining the capacity to process complex information and collaborate effectively with digital systems (Yu, 2016). In AI-intensive settings, sustained psychological strain may also lead to emotional exhaustion, further eroding motivation and job quality.

H11: AI-induced stress negatively influences employee performance.

Integrating these relationships, the strain pathway embodies a sequential threat–strain–outcome process in which AI adoption engenders job insecurity, which then heightens AI-induced stress, ultimately reducing employee performance. This serial mediation reflects the progressive erosion of psychological and cognitive resources central to COR theory, where initial perceptions of threat cascade into emotional depletion and behavioral impairment. By examining this pathway alongside the empowering process, the study captures the dual nature of AI adoption as both an enabler and a disruptor of human work experience.

H12: Perceived job insecurity and AI-induced stress serially mediate the relationship between AI adoption and employee performance.

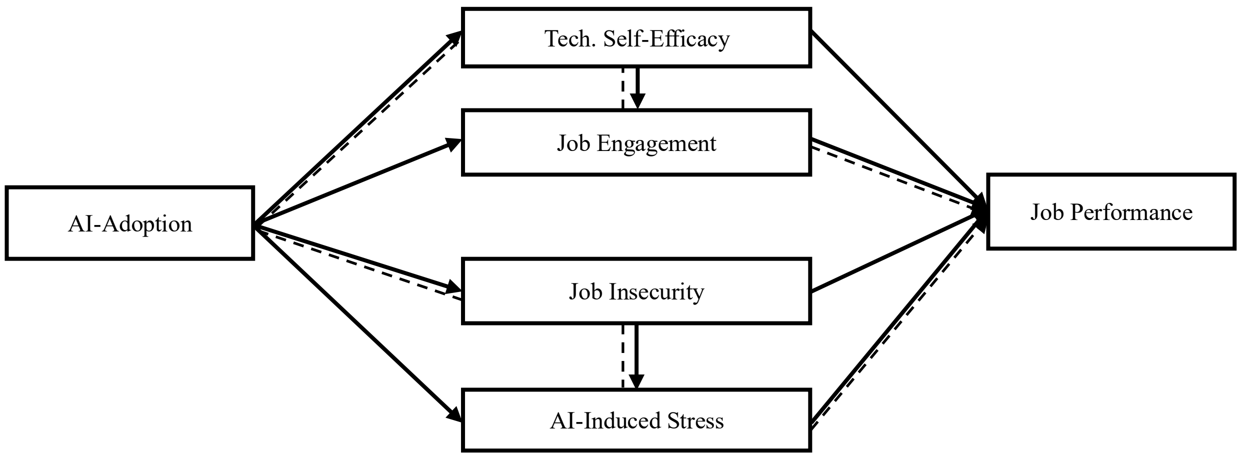

Figure 1. Research Framework

III. METHODOLOGY

In order to investigate how AI adoption affects employee performance in the Indonesian workplace context via two psychological pathways, this study used a quantitative, cross-sectional survey design. Employees of companies that had integrated AI tools or systems into their operational procedures were among the targeted population. Purposive sampling was used to choose respondents, and the inclusion criteria called for full-time workers who regularly dealt with AI-based tools like chatbots, automated analytics, or intelligent workflow systems.

Between January and March 2025, 280 valid responses were gathered. Respondents came from major Indonesian cities (e.g., Jakarta, Surabaya, Bandung, and Medan) and represented a variety of industries, including manufacturing, finance, retail, and services. All participants gave their informed consent before filling out the questionnaire, and participation was anonymous and voluntary. To put the results in context and explain the makeup of the sample, demographic data including gender, age, industry sector, and length of AI exposure were gathered.

To ensure contextual relevance for AI use across Indonesian workplaces, all constructs were measured using scales that were modified from previously validated instruments with minor wording changes. A seven-point Likert scale, with 1 denoting "strongly disagree" and 7 denoting "strongly agree," was used to record the responses. AI Adoption, Technological Self-Efficacy, Job Engagement, Perceived Job Insecurity, AI-Induced Stress, and Employee Performance were the six main reflective constructs included in the questionnaire.

Table 1 summarizes the constructs, sample items, and their respective sources.

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0. This approach was chosen because it is appropriate for complex models involving multiple mediators and allows simultaneous estimation of both measurement (outer) and structural (inner) models (Hair et al., 2024). Preliminary descriptive statistics were performed using SPSS 26 to profile the respondents and screen for missing data or outliers.

The analysis proceeded in two main stages. First, the measurement model was assessed to ensure reliability and validity of all constructs. Internal consistency reliability was evaluated through Cronbach's alpha and composite reliability (CR). Convergent validity was assessed through average variance extracted (AVE) values (Hair et al., 2024). Discriminant validity was verified using the Heterotrait–Monotrait (HTMT) ratio.

Table 1. Measurement Constructs, Sample Items, and Sources

Construct	Sample Items	Source
AI Adoption	1. The AI system helps me complete my work faster. 2. I intend to continue using AI tools regularly. 3. I find AI systems easy to use. 4. I believe AI improves the quality of my work.	(Venkatesh et al., 2003)
Technological Self-Efficacy	1. I am confident in using AI tools without help. 2. I can troubleshoot AI-related problems on my own. 3. I am calm when facing technical issues with AI. 4. I feel comfortable learning new AI systems. 5. I can complete my work using AI even if no one is around to help.	(Compeau and Higgins, 1995; Tarafdar et al., 2019)
Job Engagement	1. At my work, I feel bursting with energy. 2. I am enthusiastic about my job. 3. I am proud of the work that I do. 4. I feel happy when I am working intensely.	(Schaufeli et al., 2006)
Perceived Job Insecurity	1. I feel uncertain about my job's future. 2. I am worried that I might lose my job. 3. I fear that my job position is unstable.	(Chen and Zeng, 2021; Koen and van Bezouw, 2021)
AI-Induced Stress	1. I feel overwhelmed by the speed of AI changes. 2. I experience anxiety when interacting with AI systems. 3. Using AI drains my mental energy. 4. I feel stressed due to constant AI-related updates.	(Hou and Fan, 2024; Yang and Zhao, 2024)
Employee Performance	1.I complete my tasks efficiently. 2. I meet deadlines even when using AI tools. 3. I deliver high-quality results. 4. I can adapt to changes in work tasks caused by AI. 5. I perform well even in AI-assisted work environments.	(Aryanti and Perkasa, 2024; Hasan et al., 2024)

Second, the proposed relationships between constructs were tested by evaluating the structural model. To ensure robust inference, 5,000 resamples were used in a bootstrapping procedure to estimate path coefficients, t-values, and p-values. coefficient of determination (R2) values were used to evaluate the model's explanatory power, and effect sizes (f2) and predictive relevance (Q2) were analysed to gauge the model's predictive accuracy and substantive significance.

Variance Inflation Factor (VIF) scores at the construct level were used to assess multicollinearity. In order to test mediation effects, bias-corrected bootstrapped confidence intervals were used to examine both direct and indirect relationships among constructs. When zero was excluded from the confidence interval, indirect effects were considered significant. In line with the theoretical justification of the threat to outcome (loss orientated) and motivation to behaviour (gain orientated) processes, the sequential mediation hypotheses (H6 and H12) were investigated using a serial mediation approach. This approach made it possible for the study to evaluate the two psychological processes by which the adoption of AI affects worker performance.

Since data were collected from a single source using measures reported by respondents, potential common method bias (CMB) was addressed using both procedural and statistical remedies (Podsakoff et al., 2003). Procedurally, the questionnaire assured respondent anonymity, reduced evaluation apprehension, and randomized item order to minimize response consistency bias. Statistically, a Harman’s single-factor test showed that no single factor accounted for the majority of variance (<40%), and a latent method factor test indicated that the common method factor explained less than 5% of the total variance, suggesting that CMB was not a serious concern.

IV. RESULTS

A. Descriptive Statistics

Table 2 presents the descriptive statistics for the six key constructs examined in this study. Overall, the results indicate that respondents reported relatively high levels of AI Adoption,

Technological Self-Efficacy, Job Engagement, and Employee Performance, while Perceived Job Insecurity and AI-Induced Stress were rated comparatively lower.

Table 2. Construct Descriptive Statistics

Construct	Mean	Standard Deviation	Min	Max
AI Adoption	5.64	1.02	2	7
Technological Self-Efficacy	5.42	1.10	2	7
Job Engagement	5.78	0.94	3	7
Perceived Job Insecurity	3.12	1.18	1	6
AI-Induced Stress	3.45	1.25	1	7
Employee Performance	5.67	0.88	3	7

The mean score for AI Adoption was 5.64 (SD = 1.02), suggesting that most respondents perceived AI systems as helpful and were generally receptive to their continued use. Similarly, Technological Self-Efficacy had a mean of 5.42 (SD = 1.10), indicating that employees felt reasonably confident in their ability to work with AI tools. Job Engagement yielded the highest mean among all constructs, at 5.78 (SD = 0.94), reflecting strong psychological involvement and enthusiasm toward work among employees in AI-integrated environments.

However, the significantly lower mean of 3.12 (SD = 1.18) for perceived job insecurity indicates that, although there were worries about job loss as a result of AI, these worries were not prevalent throughout the sample. AI-Induced Stress showed a similar pattern, with a mean score of 3.45 (SD = 1.25), suggesting that AI technologies cause moderate amounts of stress. These results lend credence to the idea that, despite the potential for psychological stress, employees' overall perceptions of AI tended to be more supportive of empowerment than fear.

Finally, the mean for Employee Performance was 5.67 (SD = 0.88), implying that most respondents perceived themselves as maintaining high performance within work settings supported by AI. The relatively narrow standard deviations across most constructs suggest a moderate level of consensus among respondents. These descriptive trends align with the dual process framework of the study, where AI adoption can foster both empowering and straining psychological responses that shape work outcomes in different directions.

B. Measurement Model

The measurement model was evaluated to ensure the reliability and validity of all constructs used in this study. Table 3 presents the item loadings, Cronbach's alpha values, composite reliability (CR), and average variance extracted (AVE) for each latent construct.

Table 3. Measurement Model Results

Construct	Item Code	Loading	Cronbach's Alpha	CR	AVE
AI Adoption	AI1	0.81	0.86	0.89	0.67
	AI2	0.85			
	AI3	0.79			
	AI4	0.83			
Technological Self-Efficacy	TSE1	0.78	0.88	0.91	0.66
	TSE2	0.84			
	TSE3	0.80			
	TSE4	0.77			
	TSE5	0.82			
Job Engagement	ENG1	0.86	0.87	0.90	0.70
	ENG2	0.83			
	ENG3	0.79			
	ENG4	0.81			
Perceived Job Insecurity	JI1	0.88	0.84	0.87	0.69
	JI2	0.85			
	JI3	0.82			
AI-Induced Stress	AIS1	0.81	0.85	0.88	0.65
	AIS2	0.79			
	AIS3	0.77			
	AIS4	0.80			
Employee Performance	PERF1	0.87	0.89	0.92	0.71
	PERF2	0.84			
	PERF3	0.85			
	PERF4	0.82			
	PERF5	0.83			

All indicator loadings exceeded the recommended threshold of 0.70, indicating strong individual item reliability (Hair et al., 2019). Specifically, loadings ranged from 0.77 to 0.88 across all constructs, suggesting that each observed item loaded appropriately onto its corresponding latent variable.

Internal consistency reliability was assessed using both Cronbach's alpha and composite reliability (CR). All constructs exceeded the minimum acceptable level of 0.70 for both indicators. Cronbach's alpha values ranged from 0.84 (Perceived Job Insecurity) to 0.89 (Employee Performance), while CR values ranged from 0.87 to 0.92. These results indicate that the items within each construct demonstrated satisfactory internal consistency.

Convergent validity was confirmed through the assessment of average variance extracted (AVE). All AVE values exceeded the threshold of 0.50, with values ranging from 0.65 (AI-Induced Stress) to 0.71 (Employee Performance). This indicates that each construct accounted for more than half of the variance in its indicators, thus satisfying the requirement for convergent validity (Fornell and Larcker, 1981).

In sum, the measurement model demonstrated acceptable levels of indicator reliability, internal consistency, and convergent validity. These findings support the use of the constructs in the subsequent structural model analysis.

The results of the evaluation of discriminant validity using the Heterotrait-Monotrait (HTMT) ratio of correlations are shown in Table 4. In structural equation modelling, HTMT is thought to be a more accurate and rigorous approach to proving discriminant validity than more conventional standards like the Fornell–Larcker method (Henseler et al., 2015).

Table 4. HTMT Discriminant Validity Matrix

Construct	AI	TSE	ENG	JI	AIS	PERF
AI Adoption	1.00	0.72	0.68	0.35	0.39	0.65
Technological Self-Efficacy	0.72	1.00	0.75	0.30	0.36	0.70
Job Engagement	0.68	0.75	1.00	0.33	0.40	0.74
Perceived Job Insecurity	0.35	0.30	0.33	1.00	0.78	0.32
AI-Induced Stress	0.39	0.36	0.40	0.78	1.00	0.37
Employee Performance	0.65	0.70	0.74	0.32	0.37	1.00

Every HTMT value in the table is below the conservative cutoff point of 0.85, indicating that each construct is empirically different from the others. In particular, the HTMT ratios varied between 0.30 and 0.78. Given that job insecurity frequently leads to psychological strain in an AI-supported work environment, the strongest correlation was found between perceived job insecurity and AI-induced stress (HTMT = 0.78). Meanwhile, lower HTMT values, such as between

Technological Self-Efficacy and Perceived Job Insecurity (HTMT = 0.30), further confirm the conceptual distinction between constructs across the dual-pathway model.

These findings provide strong evidence of discriminant validity for all latent variables in the model. As such, the constructs can be interpreted as measuring distinct psychological mechanisms, which supports the robustness of the dual process framework adopted in this study.

Table 5. Variance Inflation Factor (VIF) for Latent Constructs

Construct	VIF
AI Adoption	1.94
Technological Self-Efficacy	2.08
Job Engagement	2.17
Perceived Job Insecurity	1.89
AI-Induced Stress	2.12
Employee Performance	2.21

With VIF values ranging from 1.89 to 2.21, all latent constructs showed acceptable levels of collinearity, falling well short of the generally recognised cutoff of 3.3 (Hair et al., 2021). This suggests that multicollinearity is not an issue in the structural model and that the predictor constructs are statistically independent. The findings guarantee the stability and dependability of the model by confirming that each construct makes a distinct contribution to the explanation of variance in its endogenous variables.

C. Structural Model

Table 6 reports the coefficient of determination (R^2) for each endogenous construct. R^2 indicates the proportion of variance in the dependent variable explained by its predictors. The results show that Employee Performance has the highest R^2 value at 0.68, suggesting that 68% of the variance in performance is explained by its predictors, which is considered substantial (Hair et al., 2019).

Job Engagement (R^2 = 0.57) and Technological Self-Efficacy (R^2 = 0.52) demonstrate moderate levels of explanatory power. AI-Induced Stress (R^2 = 0.41) also falls within the moderate range, indicating a reasonable predictive capacity by its antecedents. However, Perceived Job Insecurity has a relatively low R^2 value of 0.33, classified as weak, indicating that additional factors beyond AI Adoption might influence insecurity perceptions. Overall, the model demonstrates satisfactory explanatory strength, particularly in predicting job performance.

Table 7 presents model fit indices for the full structural model. The Standardized Root Mean Square Residual (SRMR) equal 0.061, well below the conservative threshold of 0.08, indicating a good overall model fit (Henseler et al., 2015).

Table 6. R^2 Values (Coefficient of Determination)

Construct	R^2	Interpretation
Job Engagement	0.57	Moderate
Technological Self-Efficacy	0.52	Moderate
AI-Induced Stress	0.41	Moderate
Perceived Job Insecurity	0.33	Weak
Employee Performance	0.68	Substantial

Additional PLS-specific fit measures such as d_ULS (0.794) and d_G (0.502) are within acceptable ranges, suggesting that the discrepancies between empirical and model-implied matrices are minimal. The RMS_theta value of 0.103 is also below the 0.12 threshold, reflecting good outer model residual quality. Lastly, the Normed Fit Index (NFI) of 0.925 exceeds the standard cutoff of 0.90, confirming excellent comparative model fit. Together, these indices provide strong evidence that the measurement and structural components of the model are well specified.

Table 7. Model Fit Indices (PLS-SEM)

Fit Index	Threshold	Model Value	Interpretation
SRMR	< 0.08 (Henseler et al., 2014)	0.061	Good fit
d_ULS	Lower is better	0.794	Acceptable
d_G	Lower is better	0.502	Acceptable
RMS_theta	< 0.12 preferred	0.103	Good model approximation quality
NFI	≥ 0.90 (acceptable)	0.925	Excellent fit

The path analysis results demonstrate that AI adoption significantly enhances technological self-efficacy among employees (β = 0.68, t = 14.32, $p < 0.001$, f^2 = 0.46), representing a large effect size. This finding indicates that the integration of artificial intelligence tools substantially strengthens employees' confidence in their capacity to engage with digital systems. This aligns with Bandura (1997) self-efficacy theory, suggesting that mastery experiences with technology reinforce belief in one's competence. Adoption of AI also has a significant positive impact on job engagement (β = 0.44, t = 6.89, $p < 0.001$, f^2 = 0.24), indicating that workers who view AI as a helpful tool are more engaged, committed, and energetic at work. These findings are consistent with the Job Demands Resources (JDR) framework, which holds that technology improves motivational states and engagement when it functions as a job resource as opposed to a demand.

Table 8. Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Decision
H1	AI Adoption → Technological Self-Efficacy	0.68	14.32	< 0.001	Supported
H2	AI Adoption → Job Engagement	0.44	6.89	< 0.001	Supported
H3	Technological Self-Efficacy → Job Engagement	0.59	11.07	< 0.001	Supported
H4	Technological Self-Efficacy → Employee Performance	0.33	5.72	0.002	Supported
H5	Job Engagement → Employee Performance	0.46	8.30	< 0.001	Supported
H6	AI Adoption → TSE → ENG → Employee Performance	0.18	4.10	0.007	Supported
H7	AI Adoption → Perceived Job Insecurity	0.39	7.24	< 0.001	Supported
H8	AI Adoption → AI-Induced Stress	0.28	5.10	0.001	Supported
H9	Perceived Job Insecurity → AI-Induced Stress	0.52	9.85	< 0.001	Supported
H10	Perceived Job Insecurity → Employee Performance	−0.21	3.78	0.004	Supported
H11	AI-Induced Stress → Employee Performance	−0.26	4.96	0.001	Supported
H12	AI Adoption → Insecurity → Stress → Employee Performance	−0.14	3.55	0.011	Supported

Additionally, there is a strong cognitive-to-motivational link between technological self-efficacy and job engagement, as evidenced by the significant increase in job engagement ($\beta = 0.59$, $t = 11.07$, $p < 0.001$, $f^2 = 0.37$). Workers are more likely to be enthusiastic and persistent in their work tasks if they believe they can use AI effectively. Conversely, there is a medium effect size of technological self-efficacy directly influencing employee performance ($\beta = 0.33$, $t = 5.72$, $p = 0.002$, $f^2 = 0.18$). This demonstrates that self-efficacy not only encourages participation but also results in noticeable increases in productivity. The direct effect of job engagement on performance ($\beta = 0.46$, $t = 8.30$, $p < 0.001$, $f^2 = 0.27$) also shows a moderately strong impact, consistent with prior empirical findings that engaged employees deliver higher quality work and display stronger organizational commitment. The sequential indirect effect from AI adoption through technological self-efficacy and job engagement on employee performance ($\beta = 0.18$, $t = 4.10$, $p = 0.007$) further supports the dual cognitive to motivational chain predicted by JD–R and Social Cognitive Theory. Although this indirect effect is statistically smaller than the direct cognitive paths, it remains practically meaningful, reflecting the layered psychological mechanisms through which technology drives performance.

At the same time, a detrimental psychological process is also noted. Adoption of AI has a moderate effect size and significantly raises perceived job insecurity ($\beta = 0.39$, $t = 7.24$, $p < 0.001$, $f^2 = 0.21$). This raises concerns about technological substitution and implies that workers may view AI as a possible threat to job continuity or skill relevance. Furthermore, there is a small-to-medium effect of AI adoption directly contributing to AI-induced stress ($\beta = 0.28$, $t = 5.10$, $p = 0.001$, $f^2 = 0.16$). This illustrates how workers may feel emotionally strained when adjusting to AI systems that are opaque and always changing. The relationship between perceived job insecurity and AI-induced stress is particularly strong ($\beta = 0.52$, $t = 9.85$, $p < 0.001$, $f^2 = 0.33$), signifying that uncertainty about employment stability acts as a key emotional amplifier, leading to intensified strain.

Both perceived job insecurity ($\beta = -0.21$, $t = 3.78$, $p = 0.004$, $f^2 = 0.12$) and AI-induced stress ($\beta = -0.26$, $t = 4.96$, $p = 0.001$, $f^2 = 0.14$) have negative and practically moderate effects on employee performance, underscoring the detrimental role of psychological strain in technology-driven environments. The negative sequential mediation from AI adoption through job insecurity and AI-induced stress to performance ($\beta = -0.14$, $t = 3.55$, $p = 0.011$) further validates the threat–strain–outcome mechanism proposed by Conservation of Resources (COR) theory. Although this indirect effect is smaller in magnitude than the positive chain, its presence highlights a persistent psychological cost that organizations must address.

From a comparative perspective, the positive chain ($\beta = 0.18$) is only marginally stronger than the negative chain ($\beta = -0.14$), suggesting that the net influence of AI adoption on performance is nearly balanced, a finding that reinforces the dual process nature of AI in the workplace. The relative effect sizes imply that while transformations enabled by artificial intelligence empowerment yields meaningful performance gains, unaddressed insecurity and stress can substantially offset these benefits. In practical terms, a one-unit increase in AI adoption corresponds to an estimated 0.18-point increase in performance via the positive pathway and a 0.14-point decrease via the negative pathway, resulting in a small but positive net gain. This nuanced equilibrium underscores the need for human-centered AI implementation strategies that strengthen technological self-efficacy and engagement while mitigating perceived threats and psychological strain.

Collectively, these findings provide robust empirical validation for the dual process model. They demonstrate that AI adoption operates simultaneously as an enabler of resource gain and a source of resource loss, shaping employee outcomes through parallel cognitive and emotional routes. The integration of the JD–R, SCT, and COR frameworks provides a theoretical basis for understanding how empowerment and strain can coexist within work environments involving artificial intelligence. Practically, these results emphasize that successful AI integration requires not only technological investment but also deliberate attention to employee capability building, transparent communication, and psychological support mechanisms to sustain both performance and well-being.

V. DISCUSSION

The current study investigated the dual psychological mechanisms through which AI adoption affects employee performance: a negative pathway involving perceived job insecurity and stress caused by AI, and a positive pathway involving technological self-efficacy and job engagement. The results validate the suggested dual process model in the context of Indonesian workplaces undergoing technological transformation, supporting each of the twelve hypotheses.

The findings demonstrate that, when combined with the right training and organisational support, AI adoption has a significant positive impact on technological self-efficacy ($\beta = 0.68$). According to Bandura's (1997) Social Cognitive Theory, which emphasises mastery experiences as the cornerstone of self-efficacy, employees who view AI tools as facilitators rather than threats grow more confident in their ability to learn the technology. The idea that psychological empowerment increases intrinsic motivation and work dedication is supported by the following relationship between self-efficacy and job engagement ($\beta = 0.59$). These results align with findings by Balalle (2024), who demonstrated that technological confidence promotes sustained engagement across digitally mediated environments. Both technological self-efficacy ($\beta = 0.33$) and job engagement ($\beta = 0.46$) significantly improve performance, reflecting the JD–R model's principle that personal and job resources jointly elevate motivational and behavioral outcomes.

Importantly, the sequential mediation effect of AI adoption on performance through job engagement and technological self-efficacy ($\beta = 0.18$), offers useful information about how strong this beneficial pathway is. Concretely speaking, through the cognitive–motivational chain, an increase of one point in the perceived adoption of AI translates into an improvement in employee performance of roughly 0.18 points. This study demonstrates the gradual but significant improvement in performance that can be attained when businesses simultaneously promote digital competency and engagement.

However, the study also identifies a detrimental psychological mechanism that reflects this process of enabling. Adoption of AI dramatically raises stress from AI ($\beta = 0.28$) and job insecurity ($\beta = 0.39$), indicating that the same technological advancement that empowers some workers can also make others uneasy. Stress is strongly predicted by job insecurity (= 0.52), resulting in a threat-strain-outcome sequence that is in line with the Conservation of Resources (COR) theory (Demerouti, 2025). This process underscores that perceptions of potential job loss or obsolescence trigger emotional exhaustion and reduced task focus. The negative indirect effect from AI adoption via insecurity and stress ($\beta = -0.14$) confirms the presence of this strain pathway. Practically, this means that a one-point increase in perceived AI adoption may lead to a 0.14-point reduction in performance through insecurity and stress, partially offsetting the positive effects.

Comparing both processes reveals that the positive chain ($\beta = 0.18$) is only slightly stronger than the negative chain ($\beta = -0.14$), indicating a near-zero net effect of AI adoption on overall performance.

This equilibrium implies that concurrent emotional stress can undermine the benefits of psychological empowerment. If companies don't control employees' affective reactions and perceptions of job threat, productivity gains from artificial intelligence-enabled transformations may plateau in practice. This finding theoretically expands on the JDR and COR frameworks by demonstrating that, depending on contextual and psychological evaluations, a single technological resource can function as both a source of motivation and stress.

The R2 for job insecurity is relatively low (0.33), despite the fact that the structural model accounts for a significant amount of the variance in important constructs (e.g., R2 = 0.65 for job engagement and R2 = 0.58 for performance). This suggests that although the adoption of AI explains a sizable portion of perceived insecurity, employees' sense of job stability is probably influenced by other contextual factors that cannot be measured. These variables can either lessen or increase feelings of insecurity during technologically driven transitions. Examples of these factors include the existence of labour unions, the perception of fairness in organisational change, and government programs on retraining and employment protection. Future research could integrate these institutional and policy-level determinants to provide a more comprehensive understanding of how structural protections interact with individual perceptions in emerging-economy settings.

Taken together, these results reveal a nuanced reality: AI adoption functions as both an enabler and a disruptor of performance, producing cognitive gains and emotional costs that coexist within the same workforce. The nearly balanced β weights underscore that technological progress does not automatically translate into productivity improvements, it depends on how effectively organizations cultivate psychological resources while minimizing threat perceptions. From a managerial perspective, this implies that technical implementation must be accompanied by approaches to organizational change that focus on people, build self-efficacy, foster engagement, and address insecurity through transparent communication and targeted reskilling programs.

In the Indonesian context, where digital transformation is advancing rapidly but labor protections and retraining mechanisms remain uneven, these findings have significant policy implications. Policymakers and business leaders should design AI integration strategies that are both innovative and inclusive, linking technological investment with workforce upskilling, emotional support programs, and participatory design. Addressing these psychosocial factors will be critical for transforming AI adoption from a source of mixed outcomes into a sustainable driver of employee performance and well-being.

VI. IMPLICATION

The study's conclusions have a number of significant ramifications for theory and practice regarding the incorporation of AI in corporate environments. Theoretically, this study adds to the growing body of literature that views the adoption of AI as a psychologically mediated process with two outcomes rather than just a technological choice. The study broadens our understanding of AI's role beyond the linear and frequently overly optimistic narratives of digital transformation by integrating both enabling and threatening psychological mechanisms. Specifically, the validation of two sequential mediational pathways one positive (via technological self-efficacy and job engagement) and one negative (via perceived job insecurity and AI-induced stress) reinforces the notion that the impact of AI is contingent on how it is experienced and interpreted by employees. This framework responds to recent scholarly calls for more nuanced approaches to studying AI in the workplace, particularly those that account for both cognitive empowerment and emotional distress.

From a practical standpoint, the study underscores the need for a balanced AI implementation strategy that deliberately addresses both the opportunities and risks of digital transformation. Organizations seeking to leverage AI for performance improvement must prioritize the development of technological self-efficacy among employees. This can be achieved through structured digital upskilling programs, inclusive design processes that involve end-users in AI deployment, and the provision of technical support systems that foster confidence and competence. Moreover, the positive role of job engagement suggests that fostering meaningful work experiences and creating environments where employees feel valued and absorbed in their roles can amplify the productivity benefits of AI.

At the same time, the confirmation of a negative pathway calls attention to the often-overlooked psychological costs of AI adoption. Perceived job insecurity and AI-induced stress emerged as significant deterrents to employee performance, which implies that even well-intentioned technological changes may backfire if employees feel excluded, devalued, or threatened. Managers must therefore invest in transparent communication strategies that clarify the purpose, scope, and implications of AI initiatives. Reassuring employees about role continuity, offering clear pathways for skill adaptation, and creating opportunities for participation in change processes can help alleviate insecurity. Additionally, establishing mental health support services and stress management programs may be necessary to mitigate the emotional burdens associated with digital disruption.

These implications are especially relevant in the Indonesian context. Many workers may experience a mixed reality of excitement and fear as the public and private sectors increasingly embrace digitalisation. The risk of job insecurity is further increased by the absence of strong institutional safeguards against technological displacement. In order to guarantee that AI development is accompanied by inclusive workforce policies, capacity-building initiatives, and labour protections that protect employee well-being while fostering innovation, organisations and policymakers must cooperate. By acknowledging and addressing the psychological dualities inherent in AI adoption, organizations can better manage the human dimensions of technological change and build more resilient, high-performing workforces.

VII.CONCLUSION

This study aimed to investigate the two different psychological mechanisms through which AI adoption affects employee performance: one positive mechanism involving job engagement and technological self-efficacy, and one negative mechanism involving perceived job insecurity and stress caused by AI. A dual process framework that captures both the enabling and constraining effects of AI integration within modern organisations is strongly supported by the empirical findings, which were obtained from 280 Indonesian employees. The findings show that when AI adoption results in increased confidence in technology use and greater engagement with work, it improves employee performance. However, adoption of AI may also jeopardise performance outcomes by elevating psychological stress and feelings of insecurity. These findings provide a more balanced and comprehensive understanding of how digital transformation shapes human behavior in the workplace, reinforcing the necessity of considering both cognitive and emotional dimensions in organizational research related to AI.

Notwithstanding the study's theoretical and practical contributions, a number of limitations must be noted. First, a cross-sectional design was used to collect the data, which limits the capacity to draw firm conclusions about the causal relationships among the constructs. It would be beneficial to conduct longitudinal research to look at how workers' psychological reactions to AI change over time, especially as they become more accustomed to the technology or deal with shifting organisational environments. Second, there is a chance of common method bias because all data were reported automatically. Future studies should think about using objective performance indicators or multi-source assessments to increase the findings' robustness, even though statistical controls and procedural remedies were used. Thirdly, although the study was carried out in Indonesia, which is a useful context for studying AI adoption in emerging economies, the results may not be as broadly applicable to other areas due to institutional and cultural factors. The dual path model would be validated in a variety of contexts if the study were repeated in other nations or sectors.

Future research could also extend the current framework by exploring potential moderating variables that shape the strength or direction of each psychological pathway. For example, leadership style, organizational culture, or digital maturity may influence whether AI is perceived as a resource or a threat. Moreover, qualitative or mixed-method studies could offer richer insights into how employees interpret and adapt to AI in their daily work routines, especially for tasks with high levels of ambiguity or technological complexity. Finally, researchers could examine how different types of AI, such as generative AI, predictive analytics, or robotic process automation, differentially affect psychological mechanisms and performance outcomes.

In conclusion, this study emphasises the need for a psychologically informed approach to digital transformation and the dual nature of AI's impact on workers. By recognising AI's potential to both empower and unnerve workers, researchers and organisations can better predict its effects and create interventions that promote technological and human resilience.

ACKNOWLEDGMENT

The author received no specific grant, financial assistance, or institutional funding for the research, authorship, or publication of this manuscript and declares no conflicts of interest related to the research, analysis, or reporting of this study. The author acknowledges the use of digital writing support tools, including QuillBot, ZeroGPT, and SciSpace. The author alone was responsible for the conception, design, data collection, analysis, and writing of this manuscript and approves the final version in its entirety. The data supporting the findings of this study are available from the author upon reasonable request, with all datasets having been anonymised to protect participant confidentiality.

REFERENCES

Achnak, S., & Vantilborgh, T. (2021). Do individuals combine different coping strategies to manage their stress in the aftermath of psychological contract breach over time? A longitudinal study. *Journal of Vocational Behavior,* 131, 103651. https://doi.org/10.1016/j.jvb.2021.103651

Agina, M. F., Khairy, H. A., Abdel Fatah, M. A., Manaa, Y. H., Abdallah, R. M., Aliane, N., Afaneh, J., & Al-Romeedy, B. S. (2023). Distributive injustice and work disengagement in the tourism and hospitality industry: Mediating roles of workplace negative gossip and organizational cynicism. *Sustainability*, 15(20), 15011. https://doi.org/10.3390/su152015011

Ali, M., Khan, T. I., Khattak, M. N., & Şener, İ. (2024). Synergizing AI and business: Maximizing innovation, creativity, decision precision, and operational efficiency in high-tech enterprises. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(3), 100352. https://doi.org/10.1016/j.joitmc.2024.100352

Aryanti, I., & Perkasa, D. H. (2024). The effect of leadership compensation and work discipline on employee performance (Study at PT Panca Putra Solusindo Jakarta). Review: *Journal of Multidisciplinary in Social Sciences*, 1(04), Article 04. https://doi.org/10.59422/rjmss.v1i04.302

Balalle, H. (2024). Exploring student engagement in technology-based education in relation to gamification, online/distance learning, and other factors: A systematic literature review. *Social Sciences & Humanities Open*, 9, 100870. https://doi.org/10.1016/j.ssaho.2024.100870

Bandura, A. (1997*). Self-efficacy: The exercise of control*. W. H. Freeman.

Castaneda, A. R., Maseeh, H. I., Surachartkumtonkun, J., Shao, W., & Thaichon, P. (2026). Impact of frontline employees' perceived benefits of artificial intelligence on AI adoption and job engagement: A meta-analysis. *International Journal of Hospitality Management*, 133, 104446. https://doi.org/10.1016/j.ijhm.2025.104446

Chen, L., & Zeng, S. (2021). The relationship between intolerance of uncertainty and employment anxiety of graduates during COVID-19: The moderating role of career planning. *Frontiers in Psychology*, 12, 694785. https://doi.org/10.3389/fpsyg.2021.694785

Chen, X., Ke, J., Zhang, X., & Chen, J. (2025). The impact of AI anxiety on employees' work passion: A moderated mediated effect model. *Acta Psychologica*, 260, 105487. https://doi.org/10.1016/j.actpsy.2025.105487

Chuang, Y.-T., Chiang, H.-L., & Lin, A.-P. (2025). Insights from the job demands–resources model: AI's dual impact on employees' work and life well-being. International *Journal of Information Management,* 83, 102887. https://doi.org/10.1016/j.ijinfomgt.2025.102887

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, 19(2), 189–211. https://doi.org/10.2307/249688

Demerouti, E. (2025). Job demands–resources and conservation of resources theories: How do they help to explain employee well-being and future job design? *Journal of Business Research,* 192, 115296. https://doi.org/10.1016/j.jbusres.2025.115296

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. International *Journal of*

Information Management, 59, 102168. https://doi.org/10.1016/j.ijinfomgt.2020.102168

Ekuma, K. (2024). Artificial intelligence and automation in human resource development: A systematic review. *Human Resource Development Review,* 23(2), 199–229. https://doi.org/10.1177/15344843231224009

Fitriani, N., & Basir, I. (2025). Understanding user acceptance of AI-powered financial advisory: A dual-process model integrating trust, satisfaction, and perceived risk. *Global Review of Tourism and Social Sciences,* 1(3), 225–239. https://doi.org/10.53893/grtss.v1i3.402

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research,* 18(1), 39–50. https://doi.org/10.1177/002224378101800104

Graham, S. (2022). Self-efficacy and language learning – what it is and what it is not. *The Language Learning Journal*. https://www.tandfonline.com/doi/abs/10.1080/09571736.2022.2045679

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review,* 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Sarstedt, M., Ringle, C. M., Sharma, P. N., & Liengaard, B. D. (2024). Going beyond the untold facts in PLS–SEM and moving forward. *European Journal of Marketing*, 58(13), 81–106. https://doi.org/10.1108/EJM-08-2023-0645

Hasan, M. R., Ray, R. K., & Chowdhury, F. R. (2024). Employee performance prediction: An integrated approach of business analytics and machine learning. *Journal of Business and Management Studies*, 6(1), 215–219. https://doi.org/10.32996/jbms.2024.6.1.14

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hou, Y., & Fan, L. (2024). Working with AI: The effect of job stress on hotel employees' work engagement. *Behavioral Sciences*, 14(11), Article 11. https://doi.org/10.3390/bs14111076

Issa, H., Jaber, J., & Lakkis, H. (2024). Navigating AI unpredictability: Exploring technostress in AI-powered healthcare systems. *Technological Forecasting and Social Change*, 202, 123311. https://doi.org/10.1016/j.techfore.2024.123311

Jaiswal, A., Arun, C. J., & Varma, A. (2022). Rebooting employees: Upskilling for artificial intelligence in multinational corporations. The *International Journal of Human Resource Management*, 33(6), 1179–1208. https://doi.org/10.1080/09585192.2021.1891114

Jamaluddin. (2025). Impact of remote working on employee productivity during COVID-19 in Indonesia: The moderating role of job level and the influence of cultural adaptability. *Global Review of Tourism and Social Sciences,* 1(2), 88–98. https://doi.org/10.53893/grtss.v1i2.356

Jerez-Jerez, M. J. (2025). A study of employee attitudes towards AI, its effect on sustainable development goals and non-financial performance in independent hotels. International *Journal of Hospitality Management*, 124, 103987. https://doi.org/10.1016/j.ijhm.2024.103987

Kassa, B. Y., & Worku, E. K. (2025). The impact of artificial intelligence on organizational performance: The mediating role of employee productivity. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(1), 100474. https://doi.org/10.1016/j.joitmc.2025.100474

Khan, M. I., Yasmeen, T., Khan, M., Hadi, N. U., Asif, M., Farooq, M., & Al-Ghamdi, S. G. (2025). Integrating Industry 4.0 for enhanced sustainability: Pathways and prospects. *Sustainable Production and Consumption*, 54, 149–189. https://doi.org/10.1016/j.spc.2024.12.012

Kim, B.-J., & Kim, M.-J. (2024). How artificial intelligence-induced job insecurity shapes knowledge dynamics: The mitigating role of artificial intelligence self-efficacy. *Journal of Innovation & Knowledge*, 9(4), 100590. https://doi.org/10.1016/j.jik.2024.100590

Koen, J., & van Bezouw, M. J. (2021). Acting proactively to manage job insecurity: How worrying about the future of one's job may obstruct future-focused thinking and behavior. *Frontiers in Psychology*, 12, 727363. https://doi.org/10.3389/fpsyg.2021.727363

Liu, S., & Mei, Y. (2026). How does artificial intelligence adoption shape employee performance? A novel exploration of mimetic artificial intelligence performance through a hybrid approach based on PLS-SEM and ANN. *Technological Forecasting and Social Change,* 222, 124387. https://doi.org/10.1016/j.techfore.2025.124387

Majrashi, K. (2025). Employees' perceptions of the fairness of AI-based performance prediction features. *Cogent Business & Management,* 12(1), 2456111. https://doi.org/10.1080/23311975.2025.2456111

Maria, I., & Riswadi, R. (2024). Artificial intelligence governance strategy in the Indonesian regulation system, offensive or defensive? Sharia Oikonomia *Law Journal*, 2(4), 233–243. https://doi.org/10.70177/solj.v2i4.1643

Medici, G., Grote, G., Igic, I., & Hirschi, A. (2023). Technological self-efficacy and occupational mobility intentions in the face of technological advancement: A moderated mediation model. *European Journal of Work and Organizational Psychology*, 32(4), 538–548. https://doi.org/10.1080/1359432X.2023.2197215

Mufaddhal, Z. (2025). Artificial intelligence and service personalization in hospitality: Impacts on guest loyalty. *Advances in Tourism Studies,* 3(1), 1–15. https://doi.org/10.53893/ats.v3i1.70

Muhammad, S. S., Dey, B. L., Kamal, M. M., Samuel, L., & Alzeiby, E. A. (2025). Digital transformation or digital divide? SMEs' use of AI during global crisis. *Technological Forecasting and Social Change*, 217, 124184. https://doi.org/10.1016/j.techfore.2025.124184

Nguyen, T.-H. (2025). Research on factors influencing the employees' digital transformation engagement and job performance in logistics companies. *Sage Open*, 15(3), 21582440251353391. https://doi.org/10.1177/21582440251353391

Papagiannidis, E., Mikalef, P., Conboy, K., & Van de Wetering, R. (2023). Uncovering the dark side of AI-based decision-making: A case study in a B2B context. *Industrial Marketing Management*, 115, 253–265. https://doi.org/10.1016/j.indmarman.2023.10.003

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Przegalińska, A., Triantoro, T., Kovbasiuk, A., Ciechanowski, L., Freeman, R. B., & Sowa, K. (2025). Collaborative AI in the workplace: Enhancing organizational performance through resource-based and task-technology fit perspectives. *International Journal of Information Management*, 81, 102853. https://doi.org/10.1016/j.ijinfomgt.2024.102853

Rožman, M., Oreški, D., & Tominc, P. (2023). Artificial intelligence supported reduction of employees' workload to increase the company's performance in today's VUCA environment. *Sustainability*, 15(6), 5019. https://doi.org/10.3390/su15065019

Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The measurement of work engagement with a short questionnaire: A cross-national study. *Educational and Psychological Measurement*, 66(4), 701–716. https://doi.org/10.1177/0013164405282471

Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, 3(1), 71–92. https://doi.org/10.1023/A:1015630930326

Schwab, K. (2017). *The fourth industrial revolution* (First U.S. edition). Crown Business.

Sidorkin, A. M. (2025). Extended executive cognition, a learning outcome for the AI age. *Computers and Education Open*, 9, 100294. https://doi.org/10.1016/j.caeo.2025.100294

Song, Y., Qiu, X., & Liu, J. (2025). The impact of artificial intelligence adoption on organizational decision-making: An empirical study based on the technology acceptance model in business management. *Systems,* 13(8), 683. https://doi.org/10.3390/systems13080683

Supiandi, S. (2024). Impact of water infrastructure, home ownership, and educational facilities on economic growth in East Java. *Global Review of Tourism and Social Sciences*, 1(1), 13–20. https://doi.org/10.53893/grtss.v1i1.320

Tarafdar, M., Cooper, C. L., & Stich, J.-F. (2019). The technostress trifecta: Techno eustress, techno distress and design. Theoretical directions and an agenda for research. *Information Systems Journal,* 29(1), 6–42. https://doi.org/10.1111/isj.12169

Ulum, A. W. (2025). Reforming bureaucracy through ethics: Strengthening institutions for sustainable development. *Global Review of Tourism and Social Sciences*, 1(3), 271–282. https://doi.org/10.53893/grtss.v1i3.414

Umair, A., Conboy, K., & Whelan, E. (2023). Examining technostress and its impact on worker well-being in the digital gig economy. *Internet Research*, 33(7), 206–242. https://doi.org/10.1108/INTR-03-2022-0214

Valtonen, A., Saunila, M., Ukko, J., Treves, L., & Ritala, P. (2025). AI and employee wellbeing in the workplace: An empirical study. *Journal of Business Research*, 199, 115584. https://doi.org/10.1016/j.jbusres.2025.115584

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. https://doi.org/10.2307/30036540

Wibowo, A., Saptono, A., Narmaditya, B. S., Effendi, M. S., Mukhtar, S., Suparno, & Shafiai, M. H. M. (2024). Using technology acceptance model to investigate digital business intention among Indonesian students. *Cogent Business & Management*, 11(1), 2314253. https://doi.org/10.1080/23311975.2024.2314253

Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change,* 201, 123251. https://doi.org/10.1016/j.techfore.2024.123251

Yang, L., & Zhao, S. (2024). AI-induced emotions in L2 education: Exploring EFL students' perceived emotions and regulation strategies. *Computers in Human Behavior,* 159, 108337. https://doi.org/10.1016/j.chb.2024.108337

Yu, R. (2016). Stress potentiates decision biases: A stress induced deliberation-to-intuition (SIDI) model. *Neurobiology of Stress*, 3, 83–95. https://doi.org/10.1016/j.ynstr.2015.12.006

Yuniawan, A., Hersugondo, H., Mas'ud, F., Latan, H., & Renwick, D. W. S. (2025). Determinants of artificial intelligence adoption in the financial services industry: Understanding employees' perspectives. International *Journal of Information Management Data Insights*, 5(2), 100371. https://doi.org/10.1016/j.jjimei.2025.100371

Zhang, S., Guo, P., Yuan, Y., & Ji, Y. (2025). Anxiety or engaged? Research on the impact of technostress on employees' innovative behavior in the era of artificial intelligence. *Acta Psychologica*, 259, 105442. https://doi.org/10.1016/j.actpsy.2025.105442

Zirar, A., Ali, S. I., & Islam, N. (2023). Worker and workplace artificial intelligence coexistence: Emerging themes and research agenda. *Technovation*, 124, 102747. https://doi.org/10.1016/j.technovation.2023.102747