

DOI: <https://doi.org/10.38035/dijemss.v8i1><https://creativecommons.org/licenses/by/4.0/>

Received: 28 July 2026 | Revised: 06 August 2026 | Accepted: 24 September 2026

Beyond Technical Utility: The Role of AI in Fostering Work-Life Balance and Psychological Empowerment among University Lecturers

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Abstract: This study investigates how university lecturers' perceptions of Artificial Intelligence (AI) influence their job performance and job satisfaction. Drawing on the Stimulus–Organism–Response (S-O-R) framework, it examines the mediating roles of Psychological Empowerment and Work–Life Balance in the relationship between lecturers' perceptions of AI—measured through Perceived Usefulness and Perceived Reliability—and their work outcomes. Survey data from 327 Indonesian lecturers were analyzed using PLS-SEM. The results show that perceived AI usefulness and reliability do not directly affect job performance or satisfaction; rather, their influence operates through Psychological Empowerment and Work–Life Balance, with Work–Life Balance serving as the strongest mediator. This indicates that AI's positive effects emerge primarily through improved empowerment and a more balanced professional and personal life. The findings highlight the importance of a human-centered approach to implementing technology in academia, suggesting that the true value of AI lies not solely in its technical capabilities but in its contribution to the holistic well-being of academic staff. Universities are therefore advised to prioritize AI strategies that actively support lecturers' empowerment and work–life balance.

Keywords: Artificial Intelligence, Psychological Empowerment, Work-Life Balance, Job Performance, Job Satisfaction

INTRODUCTION

The integration of Artificial Intelligence (AI) into higher education has catalyzed a significant transformation in academic practices. Generative AI tools, such as ChatGPT, Grammarly, and automated evaluation systems, are increasingly utilized to streamline diverse academic responsibilities, ranging from material development to complex data analysis and administrative management (Dwivedi et al., 2023; Mohan et al., 2023). While these technologies are widely valued for their potential to enhance efficiency, their rapid adoption introduces new dynamics into the professional lives of academic staff.

In the context of Indonesian higher education, lecturers face unique and intensifying pressures rooted in the Tri Dharma Perguruan Tinggi (Three Pillars of Higher Education). Lecturers are mandated to balance teaching, research, and community service simultaneously. The escalating demands for high-impact publications, student supervision, and institutional administration often disrupt work–life balance, leading to adverse effects on job satisfaction, performance, and overall well-being (Sari, 2020; Malau, 2023). Within this high-pressure environment, AI is often positioned as a technological solution capable of alleviating workloads by automating routine tasks (Bond et al., 2024).

However, the assumption that technical utility automatically translates to better professional outcomes requires critical scrutiny. Concerns regarding professional autonomy and an over-reliance on digital tools suggest that the benefits of AI are not guaranteed (Ahmad et al., 2022). It is therefore essential to understand not just whether lecturers use AI, but how their perceptions of its reliability and usefulness influence their psychological state—specifically their sense of empowerment and work–life balance—and subsequently, their job performance.

Despite the proliferation of AI research in education, existing studies have predominantly focused on student learning outcomes and pedagogical efficacy (Lee & Kwon, 2024; Wang et al., 2023). Research addressing the impact of AI on university lecturers, particularly within the context of developing countries like Indonesia, remains scarce. Addressing this critical gap, the present study employs the Stimulus–Organism–Response (S-O-R) framework to investigate the mechanism through which AI adoption influences academic staff. Specifically, this study examines how perceived AI reliability and usefulness (Stimulus) affect psychological empowerment and work–life balance (Organism), and how these internal states ultimately shape job satisfaction and performance (Response). By doing so, this research provides theoretical and practical insights to inform human-centered AI adoption strategies that support both innovation and lecturer well-being.

Beyond this general research gap, prior studies have also examined AI's impact largely through the lens of performance outcomes, giving limited attention to its psychological implications for educators—despite the fact that effective teaching performance depends substantially on lecturers' psychological well-being. Addressing these gaps, the novelty of this study lies in three key contributions. First, unlike prior AI adoption research that relies predominantly on the Technology Acceptance Model (TAM) to explain acceptance intention or usage behavior, this study reconceptualizes AI perceptions—perceived usefulness and perceived reliability—as psychological stimuli whose effects on work outcomes are transmitted through lecturers' internal states rather than through adoption intention.

Second, whereas many S-O-R applications in technology research focus on a single organismic mechanism, this study simultaneously examines two theoretically distinct mediators—psychological empowerment, representing a motivational-cognitive state, and work–life balance, representing a resource-related state—to assess their respective roles in linking AI perceptions with work outcomes. Third, by situating the model within the under-researched population of university lecturers in the Indonesian higher education context, where academic responsibilities are shaped by the Tri Dharma of Higher Education, this study extends AI adoption literature beyond its predominantly student- and Western-centric focus and demonstrates that the value of AI is realized not only through its technical utility but also through its contribution to lecturers' well-being.

Literature Review

Theoretical Framework and Rationale

This study adopts the Stimulus–Organism–Response (S-O-R) framework as its overarching lens because it explicitly models the internal psychological processing that links

environmental stimuli to behavioral responses—an emphasis well suited to explaining why AI perceptions do not translate directly into work outcomes. While the Technology Acceptance Model (TAM) effectively explains why individuals adopt technology, it stops at usage intention and offers limited insight into subsequent well-being and performance. Self-Determination Theory (SDT) illuminates the motivational quality of empowerment but does not account for the resource- and time-related conditions captured by work–life balance, whereas the Job Demands–Resources (JD-R) model foregrounds workload and resources but underspecifies the cognitive-motivational mechanism of empowerment. The S-O-R framework therefore serves as an integrative scaffold: TAM informs the operationalization of the stimuli (perceived usefulness and reliability), SDT and empowerment theory inform the psychological-empowerment organism, and JD-R logic informs the work–life-balance organism. This complementary integration allows the study to capture both the motivational and the conditional pathways through which AI shapes lecturers’ performance and satisfaction.

AI in Higher Education

Artificial Intelligence (AI) is increasingly used in higher education to support both academic and administrative functions. Among university lecturers, AI tools—such as ChatGPT for content generation, Grammarly for academic writing support, and AI-based assessment systems—have begun to be adopted to streamline tasks and enhance productivity. These technologies help reduce routine workloads and allow lecturers to focus more on higher-order responsibilities, such as curriculum development and research supervision (Zawacki-Richter et al., 2019).

Recent studies further highlight the transformative potential of AI in higher education. Dwivedi et al. (2023) noted that AI-driven platforms enhance efficiency by automating grading, providing personalized learning analytics, and supporting administrative decision-making. Similarly, Bond et al. (2024) emphasized that AI tools enable academic staff to allocate more time to mentoring and research activities, thereby improving institutional outcomes. Lee & Kwon (2024) demonstrated that AI enhances teaching innovation by supporting adaptive learning environments and fostering student engagement. These findings underscore AI’s role not only in reducing workload but also in reshaping pedagogical practices.

Nevertheless, the adoption of AI in academia is not without challenges. Concerns persist regarding excessive dependence on AI, data privacy, ethical usage, and its implications for academic integrity and autonomy. For example, Rai et al. (2023) argued that trust in AI systems remains fragile, with issues of reliability and transparency influencing user acceptance. Schmidt et al. (2025) also warned of potential risks to lecturers’ sense of professional autonomy and control when AI tools are overly integrated into academic workflows. These concerns highlight the importance of examining not only the potential benefits but also the psychological and professional consequences of AI use among lecturers.

Stimulus: Characteristics of AI

Within the S–O–R framework, AI functions as an external stimulus that shapes lecturers’ psychological and behavioral responses. In this study, two key AI characteristics—perceived usefulness and perceived reliability—are conceptualized as the primary stimuli.

Perceived usefulness is defined as the extent to which an individual believes that the use of a particular technology will improve their performance (Davis, 1989). In the academic context, lecturers may perceive AI-based tools as useful if they enhance efficiency in preparing teaching materials, conducting assessments, and supporting research activities. The Technology Acceptance Model (TAM) consistently demonstrates that perceived usefulness significantly influences both performance outcomes and job satisfaction (Bolodeoku et al.,

2022). Thus, the extent to which lecturers regard AI as useful plays a central role in determining their willingness to integrate it into their academic tasks.

Perceived reliability refers to the belief that AI systems are dependable, consistent, and accurate in performing tasks (Shin, 2021). For lecturers, the reliability of AI tools is particularly important to ensure that educational outputs—such as AI-generated feedback or instructional content—are trustworthy and aligned with academic standards. High levels of reliability strengthen trust and encourage the sustained use of AI in higher education. Conversely, a lack of perceived reliability may hinder adoption and limit the potential benefits of AI in academic settings.

Organism: Internal Psychological States

The organism component of the S-O-R model captures individuals' internal cognitive and emotional responses to external stimuli. In this study, psychological empowerment and work-life balance are considered as key organism variables.

Psychological empowerment is a motivational construct manifested in four cognitions: meaning, competence, self-determination, and impact (Spreitzer, 1995). When lecturers perceive that AI tools enhance their control over academic tasks, support meaningful work, and increase their influence within the academic environment, they experience greater empowerment. This sense of empowerment is critical for fostering motivation, professional growth, and sustained engagement in academic roles.

Work-life balance can be understood as a state of harmony between work demands and personal or family life that enables individuals to fulfill their commitments while achieving satisfaction and well-being in both domains (Christian et al., 2023). The role of technology is significant in shaping this balance, as it can either improve efficiency and flexibility or create additional pressures and disruptions. For lecturers who simultaneously manage teaching, research, administrative duties, and personal roles, AI adoption has the potential to act as both a facilitator and a challenge in achieving a sustainable work-life balance (Adisa et al., 2017).

Response: Work Outcomes

The final component of the S-O-R framework is the response, which in this study encompasses job satisfaction and job performance. Job satisfaction refers to employees' positive evaluation of and affective response to their work, reflecting the extent to which they feel satisfied with their job experiences and responsibilities (Wibowo et al., 2024). It reflects the degree of enjoyment and the sense of meaningfulness derived from one's professional role (Missye & Hosen, 2024). In the academic context, lecturers who perceive AI as supportive and empowering are more likely to report higher levels of satisfaction with their work. Prior studies suggest that technological support enhances lecturers' positive attitudes toward their jobs, fostering commitment and reducing stress (Kim & Kim, 2022).

Job performance is defined as the effectiveness with which individuals accomplish their job responsibilities. It represents the likelihood that tasks and objectives will be successfully achieved in alignment with institutional goals (Jabid et al., 2023). Within higher education, AI integration can significantly influence performance outcomes by reducing routine workloads, streamlining administrative tasks, and enhancing teaching and research effectiveness. By empowering lecturers to allocate more time and effort to high-value academic activities, AI has the potential to improve teaching quality, research productivity, and overall professional performance (Brougham & Haar, 2018).

HYPOTHESES DEVELOPMENT

The Influence of Perceived Usefulness and Perceived Reliability on Psychological Empowerment

The core idea of psychological empowerment is reflected in the cognitions of meaning, competence, autonomy, and impact (Spreitzer, 1995). This aligns with Self-Determination Theory, which emphasizes the role of tools and resources in enhancing intrinsic motivation by supporting autonomy and competence. In this regard, when lecturers perceive AI as useful for supporting their academic responsibilities—such as assessment, material preparation, or research activities—they are likely to feel more competent, autonomous, and motivated in their professional roles.

Beyond usefulness, the reliability of AI outputs also plays a crucial role in strengthening lecturers' sense of psychological empowerment. Reliable AI systems reinforce lecturers' confidence in making meaningful decisions and completing tasks independently. Moreover, dependable AI tools can encourage innovative pedagogical practices, enabling lecturers to experiment without fear of inaccuracy or failure. Thus, when lecturers perceive AI as both useful and reliable, they are more likely to feel empowered in fulfilling their academic responsibilities.

Prior studies support these arguments, showing that technological reliability positively influences users' perceptions of self-efficacy and autonomy (Spreitzer, 1995; Thomas & Velthouse, 1990). Similarly, Fan et al. (2023) found that AI significantly enhances employees' psychological empowerment. Based on this reasoning, the following hypotheses are proposed:

H1: Perceived Usefulness of AI positively influences Psychological Empowerment.

H2: Perceived Reliability of AI positively influences Psychological Empowerment.

The Influence of Perceived Usefulness and Perceived Reliability on Work-Life Balance

In addition to its effect on psychological empowerment, when lecturers perceive AI as both useful and reliable, they are more likely to integrate it effectively into their work routines, thereby fostering greater work-life balance. Work-life balance has been broadly defined as a state in which professional responsibilities do not disrupt personal life (Haar, 2013). For lecturers, repetitive administrative tasks often consume significant time, reducing opportunities for personal well-being and family engagement. However, with the adoption of AI, workflows can become more efficient, allowing tasks to be completed in a timelier manner (Meharunisa et al., 2024).

Empirical studies further support this view. Agarwal and Goel (2024) found that AI helps prevent burnout and reduces job-related stress, both of which are critical for achieving work-life balance. Thus, by alleviating workload pressures, AI contributes to a healthier integration of work and personal life. Based on this reasoning, the following hypotheses are proposed:

H3: Perceived Usefulness of AI positively influences Work-Life Balance.

H4: Perceived Reliability of AI positively influences Work-Life Balance.

The Influence of Perceived Usefulness on Job Performance and Job Satisfaction

The ultimate goal of adopting AI in higher education is to enhance academic performance and outcomes. Perceived usefulness is a central construct in the Technology Acceptance Model (TAM) (Davis, 1989), which posits it as a primary predictor of technology adoption and its subsequent benefits. For lecturers, perceiving AI as useful directly influences their ability to adapt to technological changes, thereby improving their professional performance.

Anaam et al. (2023) emphasized that perceived usefulness is a critical predictor of system performance outcomes. When lecturers perceive AI as beneficial, they are more likely to integrate it into their tasks, leading to increased teaching efficiency, research productivity, and administrative effectiveness.

Beyond performance, technology adoption also impacts job satisfaction. The effective use of technology enhances not only individual performance but also overall job satisfaction by reducing stress and improving task fulfillment. Based on this reasoning, the following hypotheses are proposed:

H5: Perceived Usefulness of AI positively influences Job Performance.

H6: Perceived Usefulness of AI positively influences Job Satisfaction.

The Influence of Perceived Reliability on Job Performance and Job Satisfaction

DeLone and McLean (2003) emphasize the importance of system quality—including reliability—in improving user satisfaction and delivering organizational benefits. Perceived reliability builds user trust, assuring them that the technology they rely on provides accurate and dependable results. Kong et al. (2023) further highlight that effective collaboration between AI and employees is only possible when reliability fosters trust. For lecturers, perceiving AI as reliable enhances their confidence in its outputs, which in turn strengthens their ability to fulfill demanding academic responsibilities. Prior studies demonstrate that reliable technology positively affects both job performance (Fadillah & Suryaningrum, 2021) and job satisfaction (Braganza et al., 2021). Based on this reasoning, the following hypotheses are proposed:

H7: Perceived Reliability of AI positively influences Job Performance.

H8: Perceived Reliability of AI positively influences Job Satisfaction.

The Mediating Role of Psychological Empowerment

Psychological empowerment mediates the effects of perceived usefulness and reliability of AI on job performance and satisfaction. AI enhances work outcomes only when it strengthens lecturers' feelings of competence, autonomy, and confidence, which in turn promotes proactive technology use and better performance. Moreover, when lecturers perceive that their work—supported by AI—creates meaningful impacts on students and the broader academic community, their job satisfaction is reinforced. Thus, improved performance and satisfaction can be understood as outcomes of enhanced psychological empowerment, which is shaped by the perceived usefulness and reliability of AI. Based on this reasoning, the following hypotheses are proposed:

H9: Perceived Usefulness of AI positively influences Job Performance through Psychological Empowerment as a mediator.

H10: Perceived Usefulness of AI positively influences Job Satisfaction through Psychological Empowerment as a mediator.

H11: Perceived Reliability of AI positively influences Job Performance through Psychological Empowerment as a mediator.

H12: Perceived Reliability of AI positively influences Job Satisfaction through Psychological Empowerment as a mediator.

The Mediating Role of Work-Life Balance

Work-life balance also mediates the effects of perceived usefulness and reliability of AI on job performance and satisfaction. AI improves outcomes when it helps lecturers manage tasks more efficiently, giving them more time for personal life and well-being, which supports a healthier work-life balance. Alhaider and Alqahtani (2025) explain that employees who successfully balance their professional and personal lives experience greater job satisfaction and, simultaneously, become more productive with higher-quality performance. In the academic context, the ability of lecturers to manage work and life demands effectively, supported by AI, contributes not only to improved well-being but also to enhanced performance and satisfaction.

Based on this reasoning, the following hypotheses are proposed:

H13: Perceived Usefulness of AI positively influences Job Performance through Work-Life Balance as a mediator.

H14: Perceived Usefulness of AI positively influences Job Satisfaction through Work-Life Balance as a mediator.

H15: Perceived Reliability of AI positively influences Job Performance through Work-Life Balance as a mediator.

H16: Perceived Reliability of AI positively influences Job Satisfaction through Work-Life Balance as a mediator.

Research Model

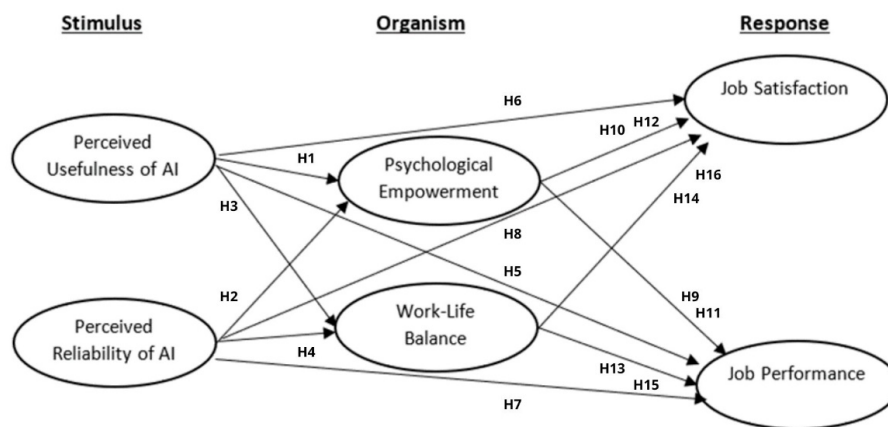


Figure 1. Research Model

METHODS

Research Design

This study adopts a quantitative research approach using a survey-based design to empirically test the proposed conceptual model grounded in the Stimulus–Organism–Response (S-O-R) framework. To test these relationships, Structural Equation Modeling (SEM) with a Partial Least Squares (PLS) approach is employed.

Data Collection Procedure

The survey was administered online using Google Forms and distributed through email and academic networks, including LinkedIn, faculty communities on WhatsApp, Facebook, Instagram, and Telegram. Data collection was conducted over a four-week period. Participation was voluntary and fully anonymous. Ethical considerations, including informed consent and the confidentiality of responses, were strictly maintained.

The population of this study consists of university lecturers in Indonesia who have experience using AI-based tools in their professional tasks, including teaching, research, and academic administration. A purposive sampling technique was employed to select respondents who had interacted with generative AI tools (e.g., ChatGPT, Grammarly, Quillbot) for academic purposes.

The final sample consisted of 327 valid responses. Given the complexity of the proposed structural model, the adequacy of this sample should be evaluated using an appropriate statistical power analysis rather than relying solely on the ten-times rule. Purposive sampling was utilized to collect data from 332 respondents, of whom 327 met the established inclusion criteria and were subsequently included in the analytical phase.

Measures

Instrument Development

All measurement items were adapted from previously validated scales in the literature and slightly modified to fit the context of AI use by university lecturers. Each construct was measured using a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree. Constructs and example items include:

- Perceived Usefulness of AI (adapted from Davis, 1989): e.g., “Using AI tools helps me work more efficiently.”
- Perceived Reliability of AI (adapted from McKnight et al., 2002): e.g., “I believe AI tools provide consistent and reliable results.”
- Psychological Empowerment (adapted from Spreitzer, 1995): e.g., “Using AI tools makes me feel more capable in carrying out my academic tasks.”
- Work-Life Balance (adapted from Haar, 2013): e.g., “My work responsibilities do not interfere with my personal life.”
- Job Satisfaction (adapted from Spector, 1985): e.g., “I am satisfied with my current academic work.”
- Job Performance (adapted from Williams & Anderson, 1991): e.g., “I consistently meet the performance expectations of my institution.”

Instrument Testing

The developed instrument produced 24 indicators, with each variable measured using 4 indicators. To ensure the instrument was comprehensible and appropriate for use, two testing procedures were performed.

The first procedure was a readability assessment using Aiken’s V method, applying a threshold value of ≥ 0.80 to determine whether the instrument was adequately comprehensible (Azwar, 2014). Data were collected from 20 respondents, who were asked to indicate whether each item was clearly understood. The results revealed that all indicators obtained V values ≥ 0.80 , indicating that the entire instrument was well comprehended by the respondents.

The second procedure was a common method bias test, in which the instrument was re-evaluated to ensure the absence of common method bias. This assessment was conducted using the Full Collinearity VIF approach. According to Kock (2015), Common Method Bias can be ruled out when the VIF values for all constructs are below 3.3. The results showed that all VIF values were below the threshold of 3.3, suggesting that common method bias was unlikely to pose a serious concern based on the full collinearity assessment.

RESULTS AND DISCUSSION

Results

Respondent Demographics

Table 1 presents the demographic characteristics of all respondents.

Table 1. Respondent Demographic Characteristics

Respondent	Category	Frequency	Percentage
Gender	Male	167	51.07
Gender	Female	160	48.93
Age	< 30 years	53	16.21
Age	30 - 39 years	181	55.35
Age	40 - 49 years	65	19.88
Age	50 - 59 years	26	7.95
Age	> 60 years	2	0.61
Place of Origin	Domiciled in Java Island	180	55.05
Place of Origin	Domiciled Outside Java Island	147	44.95

Type of Higher Education	State University	89	27.22
Type of Higher Education	Private University	238	72.78
Academic Position	Assistant Professor	124	37.92
Academic Position	Associate Professor	122	37.31
Academic Position	Full Professor	19	5.81
Academic Position	Senior Lecturer	1	0.31
Academic Position	Not Yet Promoted to JAD	61	18.65
Length of AI Usage	< 6 months	31	9.48
Length of AI Usage	6 months - 1 year	106	32.42
Length of AI Usage	> 1 year	190	58.10

Source: Research data (2026)

Measurement Model Evaluation

Convergent Validity

Convergent validity serves to confirm that the indicators designated to measure a specific construct are indeed highly correlated and represent the same underlying concept. According to the guidelines established by Hair et al. (2019), convergent validity is achieved when two primary criteria are satisfied: 1) all indicator outer loadings must be greater than the recommended threshold of 0.70, and 2) the Average Variance Extracted (AVE) for each construct must be 0.50 or higher. A high outer loading signifies that the indicator is a strong representative of the construct, while an AVE of 0.50 or more indicates that the construct explains more than half of the variance of its indicators.

Table 2. Results of Convergent Validity Test

Construct	Indicator	Outer Loading	Average Variance Extracted (AVE)
Perceived Usefulness	PU1	0.859	0.759
Perceived Usefulness	PU2	0.886	0.759
Perceived Usefulness	PU3	0.864	0.759
Perceived Usefulness	PU4	0.875	0.759
Perceived Reliability	PR1	0.831	0.723
Perceived Reliability	PR2	0.853	0.723
Perceived Reliability	PR3	0.876	0.723
Perceived Reliability	PR4	0.840	0.723
Psychological Empowerment	PE1	0.839	0.738
Psychological Empowerment	PE2	0.880	0.738
Psychological Empowerment	PE3	0.858	0.738
Psychological Empowerment	PE4	0.859	0.738
Work-Life Balance	WLB1	0.808	0.751
Work-Life Balance	WLB2	0.839	0.751
Work-Life Balance	WLB3	0.917	0.751
Work-Life Balance	WLB4	0.898	0.751
Job Performance	JP1	0.885	0.788
Job Performance	JP2	0.905	0.788
Job Performance	JP3	0.860	0.788
Job Performance	JP4	0.900	0.788
Job Satisfaction	JS1	0.814	0.741
Job Satisfaction	JS2	0.908	0.741
Job Satisfaction	JS3	0.883	0.741
Job Satisfaction	JS4	0.836	0.741

Source: SmartPLS Output (2026)

As presented in Table 2, the analysis results indicate the model demonstrates strong convergent validity.

Discriminant Validity

Discriminant validity is assessed to determine whether the constructs in the model are empirically distinct from one another and capture conceptually different phenomena. This was evaluated using two established methods: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations. According to the Fornell-Larcker criterion, the square root of each construct's AVE (bolded diagonal values in Table 2) should be greater than its correlation with any other construct in the model. For the HTMT ratio, values should ideally be below the threshold of 0.90 to confirm that constructs are distinct (Henseler et al., 2015).

Table 3. Fornell-Larcker Criterion

	JP	JS	PE	PR	PU	WLB
JP	0.888					
JS	0.785	0.861				
PE	0.611	0.598	0.859			
PR	0.492	0.507	0.657	0.850		
PU	0.586	0.537	0.639	0.610	0.871	
WLB	0.743	0.731	0.606	0.593	0.576	0.867

Source: SmartPLS Output (2026)

Table 4. Heterotrait-Monotrait (HTMT) Ratio

	JP	JS	PE	PR	PU	WLB
JP						
JS	0.888					
PE	0.785	0.861				
PR	0.611	0.598	0.859			
PU	0.492	0.507	0.657	0.85		
WLB	0.586	0.537	0.639	0.61	0.871	

Source: SmartPLS Output (2026)

The discriminant validity results should be carefully rechecked because the values reported in Table 4 appear to require verification before conclusions regarding construct distinctiveness can be drawn.

Reliability

The internal consistency reliability of the measurement scales was assessed using both Cronbach's Alpha (CA) and Composite Reliability (CR). Both metrics evaluate how well the indicators for a construct measure the same underlying concept. A construct is considered to have adequate reliability if both values are above the commonly accepted threshold of 0.70.

Table 5. Reliability Test Results

Construct	Cronbach's Alpha (CA)	Composite Reliability (CR)
Perceived Usefulness	0.894	0.926
Perceived Reliability	0.872	0.912
Psychological Empowerment	0.882	0.919
Work-Life Balance	0.889	0.923
Job Performance	0.910	0.937
Job Satisfaction	0.883	0.920

Source: SmartPLS Output (2026)

As detailed in Table 5, all constructs demonstrated high levels of reliability.

Structural Model Evaluation

Following the assessment of the measurement model, the structural model was evaluated by examining the coefficient of determination (R^2), predictive relevance (Q^2), and effect size (f^2) to assess its explanatory power, predictive capability, and the relative contribution of each exogenous construct.

The results of the coefficient of determination (R^2 and adjusted R^2) indicate that the proposed model demonstrates moderate to substantial explanatory power. Job Performance ($R^2 = 0.611$) and Job Satisfaction ($R^2 = 0.576$) exhibited the highest R^2 values, indicating that the exogenous constructs explained 61.1% and 57.6% of the variance in these endogenous variables, respectively. According to Chin (1998), these values represent moderate to substantial explanatory power. Meanwhile, Psychological Empowerment ($R^2 = 0.521$) and Work–Life Balance ($R^2 = 0.425$) also demonstrated moderate explanatory power, suggesting that the model adequately explains the variance across all endogenous constructs.

The effect size (f^2) analysis revealed varying levels of contribution among the exogenous constructs. Following Cohen’s (1988) guidelines, f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively. Work–Life Balance demonstrated a large effect on both Job Performance ($f^2 = 0.438$) and Job Satisfaction ($f^2 = 0.400$), indicating that it is the most influential predictor in the structural model. Perceived Reliability and Perceived Usefulness showed medium effects on Psychological Empowerment ($f^2 = 0.237$ and 0.188 , respectively) and medium effects on Work–Life Balance ($f^2 = 0.162$ and 0.126 , respectively). In contrast, their direct effects on Job Performance and Job Satisfaction were small to negligible ($f^2 = 0.001$ – 0.053), suggesting that the influence of AI perception constructs on work outcomes is primarily transmitted through Psychological Empowerment and Work–Life Balance, consistent with the Stimulus–Organism–Response (S-O-R) framework.

The predictive relevance (Q^2) values for all endogenous constructs were positive, ranging from 0.313 to 0.465, indicating that the model possesses satisfactory predictive relevance. Based on the guidelines proposed by Hair et al. (2019) the Q^2 values for Job Performance and Job Satisfaction (both > 0.35) indicate high predictive relevance, whereas the values for Psychological Empowerment ($Q^2 = 0.377$) and Work–Life Balance ($Q^2 = 0.313$) indicate moderate to high predictive relevance. Overall, the positive Q^2 values indicate that the model demonstrates predictive relevance for the endogenous constructs within the PLS-SEM assessment.

After establishing the adequacy of the structural model, hypothesis testing was conducted to examine the significance of the proposed relationships among constructs. The significance of the path coefficients (β) was assessed using a bootstrapping procedure with 5,000 resamples. This procedure generated T-statistics and P-values to determine whether each hypothesized relationship was statistically significant. A hypothesis was considered supported when the corresponding P-value was below the 0.05 significance threshold.

Table 6. Hypothesis Testing Results

H	Relationship	Path (β)	T-Stats	P-Values	Decision
H1	PU -> PE	0.379	7.145	0.000	Supported
H2	PR -> PE	0.425	8.230	0.000	Supported
H3	PU -> WLB	0.341	5.369	0.000	Supported
H4	PR -> WLB	0.385	6.256	0.000	Supported
H5	PU -> JP	0.183	3.711	0.000	Supported
H6	PU -> JS	0.090	1.641	0.101	Not Supported
H7	PR -> JP	-0.096	1.561	0.119	Not Supported
H8	PR -> JS	-0.021	0.384	0.701	Not Supported
H9	PU -> PE -> JP	0.082	3.249	0.001	Supported
H10	PU -> PE -> JS	0.081	3.292	0.001	Supported
H11	PR -> PE -> JP	0.092	3.419	0.001	Supported
H12	PR -> PE -> JS	0.091	3.202	0.001	Supported
H13	PU -> WLB -> JP	0.192	4.389	0.000	Supported
H14	PU -> WLB -> JS	0.191	4.676	0.000	Supported
H15	PR -> WLB -> JP	0.217	5.335	0.000	Supported
H16	PR -> WLB -> JS	0.217	5.422	0.000	Supported

Source: SmartPLS Output (2026)

Hypothesis testing reveals a direct relationship between Perceived Usefulness and lecturers' Psychological Empowerment. Hypothesis 1 (H1) confirms that Perceived Usefulness positively affects Psychological Empowerment ($\beta = 0.379$, $t = 7.145$, $p < 0.001$). Similarly, Hypothesis 2 (H2) demonstrates that Perceived Reliability influences Psychological Empowerment ($\beta = 0.425$, $t = 8.230$, $p < 0.001$). This research supports Fan et al. (2023), who found that AI usage influences employee psychological empowerment. AI creates psychological well-being, making employees feel happier and more prosperous (Sumantri et al., 2024). Most respondents reported that AI increases their work confidence, decision-making independence, and job control.

Positive perceptions of AI usefulness and reliability correlate with higher psychological empowerment levels. When AI perceptions enhance psychological empowerment, Job Performance improves. Hypothesis 9 (H9) confirms that psychological empowerment mediates the relationship between Perceived Usefulness and Job Performance ($\beta = 0.082$, $t = 3.249$, $p = 0.001$). Hypothesis 11 (H11) demonstrates similar mediation effects ($\beta = 0.092$, $t = 3.419$, $p = 0.001$). These results align with Fan et al. (2023), who found psychological empowerment mediates AI usage and Job Performance relationships.

Additionally, direct effects exist between Perceived Usefulness and Job Performance (Hypothesis 5: $\beta = 0.183$, $t = 3.711$, $p < 0.001$), supporting Anaam et al. (2023). The significant indirect effect through psychological empowerment, together with the significant direct effect of perceived usefulness on job performance, indicates partial mediation for the PU–PE–JP pathway. Conversely, Perceived Usefulness shows no direct effect on Job Satisfaction (Hypothesis 6: $\beta = 0.090$, $t = 1.641$, $p = 0.101$), supporting Chuang et al. (2025) findings on AI efficacy. Effects emerge only through psychological empowerment mediation. Hypothesis 10 (H10) confirms psychological empowerment mediates Perceived Usefulness–Job Satisfaction relationships ($\beta = 0.081$, $t = 3.292$, $p = 0.001$). Hypothesis 12 (H12) demonstrates similar mediation between Perceived Reliability and Job Satisfaction ($\beta = 0.091$, $t = 3.202$, $p = 0.001$). These findings suggest lecturers achieve job satisfaction only when psychologically empowered through positive AI perceptions.

Furthermore, this study found that Perceived Usefulness and Perceived Reliability also influence Work-Life Balance. The testing results of Hypothesis 3 (H3) show that Perceived Usefulness has a positive effect with a coefficient of 0.341, t-statistic of 5.369, and p-value of 0.000. The same results are also shown by the testing of Hypothesis 4 (H4), which found that Perceived Reliability also has a positive effect with a coefficient of 0.385, t-statistic of 6.256, and p-value of 0.000. Both results indicate that the more AI is perceived as useful and reliable, the more it helps lecturers achieve work-life balance. This finding is consistent with previous research by Meharunisa et al. (2024), which shows that AI capabilities and infrastructure influence work-life balance.

If balance between personal life and work can be achieved, then their performance and job satisfaction will also improve. The hypothesis testing results of Hypothesis 13 (H13) and Hypothesis 14 (H14) show that Work-Life Balance successfully strengthens and mediates the relationship between Perceived Usefulness and Job Performance and Job Satisfaction. Perceived Usefulness had a significant direct association with Job Performance ($\beta = 0.183$, $p < 0.001$), while the indirect effect through Work–Life Balance was also significant ($\beta = 0.192$, $p < 0.001$). These coefficients represent distinct direct and indirect effects and should not be interpreted as evidence that the direct effect “strengthened” from 0.183 to 0.192 after mediation. Meanwhile, in the H6 test, no direct influence of Perceived Usefulness on Job Satisfaction was found. The influence was only found after being mediated by Work-Life Balance as explained in the H14 test.

This study also found that Work-Life Balance successfully mediates the influence of Perceived Reliability on Job Performance and Job Satisfaction. This is shown by the testing

results of Hypothesis 7 (H7) and Hypothesis 8 (H8), which explain that Perceived Reliability does not directly affect Job Performance and Job Satisfaction. The influence is only found after being mediated by Work-Life Balance as explained in the testing of Hypothesis 15 (H15) and Hypothesis 16 (H16). The testing of both hypotheses also shows the highest coefficient values in the overall research model.

Discussion

Perceived Reliability showed a somewhat larger path coefficient to Psychological Empowerment than Perceived Usefulness. This pattern may suggest that reliability is particularly relevant to lecturers' sense of empowerment; however, the present analysis does not directly test whether lecturers prioritize accuracy over efficiency. This pattern reflects the high-stakes nature of academic work where errors in teaching, research, or assessment carry severe consequences. In academic work, concerns about the accuracy and reliability of AI outputs may be particularly salient because errors can affect teaching, assessment, and research activities. This explains why lecturers remain selective and cautious in AI adoption despite recognizing its potential benefits. The emphasis on reliability over usefulness suggests that institutional AI implementation strategies must prioritize system accuracy and dependability to gain faculty trust and adoption.

A critical finding is that AI perceptions do not directly improve job satisfaction—effects emerge exclusively through psychological empowerment. This challenges conventional technology adoption models and reveals that satisfaction derives not from tools themselves, but from the competence and autonomy they enable. Lecturers must internalize AI capabilities as extensions of their professional identity before experiencing satisfaction gains, supporting Chuang et al. (2025). The partial mediation observed for performance outcomes indicates dual pathways: AI directly facilitates task completion while building psychological resources. The absence of significant direct effects on Job Satisfaction, together with significant indirect effects through the proposed mediators, suggests that the relationship between AI perceptions and Job Satisfaction may operate primarily through lecturers' internal psychological and work-life experiences. This underscores that technology implementation in knowledge work requires psychological engagement, not merely technical proficiency.

The most consequential finding is that work-life balance mediates all effects of perceived reliability on outcomes, with no direct relationships observed. This reveals that lecturers evaluate AI primarily through a sustainability lens: does this technology help maintain a viable, healthy professional life? The highest coefficients in the model occur through work-life balance pathways, indicating that quality of life considerations supersede even psychological empowerment as motivational drivers. This dominance reflects current higher education realities where faculty face escalating workloads, administrative burdens, and productivity pressures. AI's promise of reclaiming personal time resonates more powerfully than abstract professional empowerment. As documented by Meharunisa et al. (2024), AI reduces time spent on routine tasks—grading, scheduling, administrative reporting—creating temporal and cognitive space for personal life. This reduction in workload pressure decreases stress and enables sustainable work patterns (Agarwal & Goel, 2024). The strengthening effect when work-life balance mediates usefulness-performance relationships indicates synergistic benefits: AI not only makes work efficient but makes life manageable, creating positive feedback loops where lecturers with balanced lives approach professional responsibilities with renewed energy and focus.

Analysis employing the Stimulus-Organism-Response (S-O-R) theoretical framework provides comprehensive understanding of the psychological mechanisms underlying AI adoption in academic contexts. In this model, Perceived Usefulness and Perceived Reliability function as external stimuli that trigger cognitive and affective processes in lecturers. These

stimuli do not directly produce behavioral responses; rather, they are first processed through two distinct organism mechanisms: psychological empowerment and work-life balance. Both mechanisms act as internal states that transform technological perceptions into psychological and conditional changes before generating responses in the form of job performance and job satisfaction.

The first pathway through psychological empowerment represents professional identity transformation. When lecturers perceive AI as useful and reliable (stimulus), they experience changes in internal psychological states characterized by enhanced self-confidence, sense of competence, and decision-making autonomy (organism). This psychological transformation subsequently triggers positive responses manifested as improved job performance and job satisfaction. This S-O-R process explains why effects are not direct—lecturers must first internalize AI capabilities as components of their professional competence before technological benefits can be maximized. The partial mediation identified indicates that although direct pathways exist from stimulus to response for performance, pathways through organism remain significant and essential, particularly for satisfaction outcomes that entirely depend on this psychological transformation.

The second pathway through work-life balance represents conditional and lifestyle transformation. Positive perceptions toward AI (stimulus) trigger changes in organism characterized by reduced workload, temporal flexibility, decreased stress levels, and more balanced time allocation between professional and personal life. This organism state subsequently generates responses in the form of optimal performance and enhanced job satisfaction. Notably, this pathway demonstrates stronger coefficients, indicating that conditional transformation exerts greater influence than psychological transformation in academic contexts. These findings suggest that work-life balance represents an important mechanism linking positive AI perceptions with job performance and job satisfaction and may play a particularly salient role in the academic work context.

The dominance of the work-life balance pathway in this S-O-R model provides critical insights into how lecturers process and respond to AI technology. Unlike routine work where technological stimuli can directly produce productivity responses, academic work requires more fundamental organism transformation. Lecturers require not only the capability to complete tasks more efficiently (direct response), but they need changes in life conditions that enable long-term career sustainability (response through organism). The significant indirect effects of Perceived Reliability through the organism variables, alongside its nonsignificant direct effects on the work outcomes, support the proposed indirect mechanism within the S-O-R framework.

The stronger influence of the work-life balance pathway suggests that AI's transformative potential lies in enabling sustainable academic careers rather than merely enhancing productivity. In an era of widespread faculty burnout, technologies that restore balance address fundamental needs at the organism level, thereby enabling optimal responses. However, this potential requires robust stimuli—AI systems demonstrating sufficient reliability to justify lecturer trust and willingness to delegate cognitive tasks. Thus, the S-O-R framework reveals that successful AI implementation in academia is not determined solely by stimulus strength, but by the ability of such stimuli to generate meaningful organism transformation, which in turn produces sustainable performance and satisfaction responses.

These findings show that AI's impact is not purely technological but depends on how it reshapes lecturers' psychological and lifestyle experiences. The lack of direct effects highlights that AI creates value mainly through work-life balance and psychological empowerment. Reliable, accurate AI systems that free time and reduce cognitive load are essential for improving both performance and satisfaction. Thus, higher education institutions should

prioritize system reliability while recognizing that successful adoption hinges on supporting well-being, not just efficiency.

A central theoretical question raised by these results is why work–life balance emerged as a stronger mediator than psychological empowerment. Two explanations are advanced. One possible interpretation is that time and cognitive energy constitute important resources for lecturers, such that perceived improvements in work–life balance may be particularly relevant in managing demanding academic responsibilities. Empowerment is thus a higher-order state contingent on the more basic resource condition of balance, which explains its comparatively weaker and partly redundant mediation. Second, in the Indonesian higher-education context, where the Tri Dharma simultaneously imposes teaching, research, and community-service obligations, chronic role overload makes work–life balance the most salient and immediately felt benefit of AI, so lecturers evaluate the technology primarily through a sustainability lens rather than through abstract empowerment. Theoretically, this positions work–life balance as a necessary conditional mechanism within the S-O-R chain and implies that AI implementation in higher education will not improve performance or satisfaction unless it first restores balance, even where empowerment is present.

Theoretical and Practical Implications

Theoretically, this study strengthens TAM by showing that perceived usefulness and reliability shape not only technology acceptance but also psychological empowerment and work–life balance, which then enhance job performance and satisfaction. By integrating TAM with the S–O–R framework, the findings highlight reliability as a key determinant in AI contexts and identify psychological empowerment and work–life balance as core mediators linking AI perceptions to positive outcomes.

Practically, the results guide universities to prioritize reliable, accurate AI systems, manage teaching and administrative workloads, streamline academic processes, and ensure institutional support that reduces pressure rather than adding to it. Continuous digital literacy training, empowerment programs, and human-centered AI policies are essential for fostering confidence, well-being, and sustainable academic performance.

CONCLUSION

This S-O-R (Stimulus-Organism-Response) analysis demonstrates that Artificial Intelligence (AI) technology significantly influences lecturers' job performance and satisfaction through two distinct mediation mechanisms: psychological empowerment and work-life balance as organisms mediating stimulus-response relationships. In this S-O-R model, Perceived Usefulness and Perceived Reliability function as stimuli, with lecturers prioritizing AI reliability over usefulness.

Psychological empowerment operates as an effective mediator through partial mediation for job performance and full mediation for job satisfaction, while work-life balance demonstrates the strongest mediating role for both AI perceptions. Work-life balance successfully mediates perceived reliability relationships with performance and satisfaction despite no direct effects. Within the proposed S-O-R framework, perceived AI usefulness and reliability were positively associated with Psychological Empowerment and Work–Life Balance, which in turn were associated with Job Performance and Job Satisfaction.

These findings emphasize the importance of holistic approaches in academic AI implementation. Successful AI adoption depends not only on technical aspects like usefulness and reliability, but also on impacts on psychological conditions and work-life balance. Work-life balance emerges as a key determinant of AI effectiveness in enhancing lecturer performance and satisfaction, indicating that technology benefits maximize when contributing to individual overall well-being. This research confirms that AI usage must remain human-

dependent, with positive responses maximized when lecturers feel psychologically empowered by AI usage perceptions.

This demonstrates that human agency remains central to maximizing AI potential. Consequently, higher education institutions must ensure AI implementation focuses not only on productivity enhancement but also on creating work environments supporting psychological empowerment and work-life balance for lecturers.

Limitations

This study has several limitations that should be acknowledged. First, although purposive sampling was appropriate for selecting lecturers with prior experience using generative AI (e.g., ChatGPT) in academic or administrative activities, it limits the representativeness of the sample and introduces the potential for self-selection bias. Lecturers who voluntarily adopt AI may possess characteristics such as higher digital literacy, greater openness to technological innovation, or heavier workloads that motivate the use of more efficient tools. These characteristics may independently influence the relationships among the study variables, beyond the effects of AI usage itself. Second, the findings should be interpreted within the Indonesian higher education context, where lecturers operate under the Tri Dharma framework and where work culture is generally more collectivistic and hierarchical than in many other countries.

Consequently, constructs such as psychological empowerment and work-life balance, as well as the relatively stronger mediating role of work-life balance observed in this study, may reflect the specific workload structure, institutional environment, digital infrastructure, and AI governance policies of Indonesia rather than being universally applicable. Third, the cross-sectional design limits causal inference, while the reliance on self-reported measures may introduce common-method bias despite the collinearity checks performed. Therefore, future research should employ probability sampling, longitudinal or mixed-method approaches, and cross-national comparative designs to enhance the robustness, causal validity, and generalizability of the proposed model across different educational and cultural contexts.

Theoretical Contribution and Practical Recommendations

Beyond its empirical findings, this study makes a distinct theoretical contribution to the AI-adoption literature in higher education. By integrating TAM-based stimulus constructs into an S-O-R framework and modeling psychological empowerment and work-life balance as parallel mediators, it demonstrates that the impact of AI is transmitted through internal psychological and conditional states rather than through adoption per se. In doing so, it advances the field beyond acceptance-focused models toward a well-being-centered explanation of technology value and identifies work-life balance as a key mechanism through which AI creates value in knowledge-intensive work settings. These theoretical insights also provide a basis for practical strategies to maximize the benefits of AI in higher education.

These findings provide clear guidance for university leaders and policymakers in implementing AI effectively within higher education. First, institutions should establish comprehensive AI governance policies that clearly define the permissible use of AI in teaching, assessment, research, and administrative activities, while incorporating standards for transparency, accountability, academic integrity, data privacy, algorithmic fairness, and appropriate human oversight. Given that lecturers place greater importance on AI reliability than usefulness, universities should adopt a reliability-first approach by approving only AI platforms that have been rigorously validated for accuracy, consistency, and dependability before large-scale implementation. Furthermore, the finding that perceived usefulness and perceived reliability influence job performance and job satisfaction only indirectly—through psychological empowerment and work-life balance, with work-life balance emerging as the

strongest mediating mechanism—suggests that investment in AI technology alone is insufficient. To ensure that AI-generated efficiency translates into meaningful organizational benefits, universities should complement technological investments with human-centered policies, including continuous digital literacy and AI competency training, structured empowerment initiatives, flexible working arrangements, the automation of routine administrative tasks, equitable workload allocation, and adaptive leave and rest policies. Such measures would enable the time savings generated by AI to be converted into genuine improvements in lecturers' work-life balance rather than being absorbed by additional work demands, thereby strengthening faculty well-being, sustaining trust in AI, and ultimately enhancing long-term job performance and job satisfaction.

AUTHOR CONTRIBUTIONS

All authors contributed significantly to this study, including research conceptualization, methodology development, data collection, data analysis, and manuscript preparation. All authors have read and approved the final version of the manuscript.

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