

Artificial Intelligence in HRM: Threat or Opportunity for Employee Engagement?

Ida Bagus Udayana Putra¹, Made Setini^{1*}, Ida Bagus Nyoman Udayana²,
Mochamad Soelton³, Olivia Imaculada do Rêgo Sarmento¹

¹Warmadewa University, Jl. Terompong No. 24, Denpasar City, Bali 80239, Indonesia

²University of Sarjanawiyata Tamansiswa, Jl. Batikan, Yogyakarta 55167, Indonesia

³Mercu Buana University, Jl. Meruya Selatan No.1, Jakarta 11650, Indonesia

*Corresponding Email: setini@warmadewa.ac.id

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The rapid digital transformation in higher education has encouraged universities to adopt Artificial Intelligence-based Human Resource Management (AI-based HRM) systems. While AI improves administrative efficiency and objectivity, it also raises concerns regarding job security and role adaptation, potentially influencing employee engagement. This study aims to examine the effect of AI-based HRM and organizational support on employee engagement, with AI perception as a mediating variable. A quantitative explanatory design was employed, using survey data from 250 lecturers and education staff at universities that implement AI-based e-HRM systems. Data were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM). The results indicate that AI-based HRM ($\beta = 0.231$; $p < 0.001$) and organizational support ($\beta = 0.264$; $p < 0.001$) significantly influence employee engagement. AI perception has the strongest direct effect on engagement ($\beta = 0.419$; $p < 0.001$) and partially mediates the relationships between AI-based HRM, organizational support, and engagement. The model explains 56.9% of the variance in employee engagement ($R^2 = 0.569$). These findings suggest that positive employee perception of AI as an opportunity rather than a threat is a crucial psychological mechanism in enhancing sustainable engagement in higher education institutions.

Keywords: Artificial Intelligence-Based HRM; Employee Engagement; Higher Education; Organizational Support; Perception of Artificial Intelligence

INTRODUCTION

Universities in Indonesia are facing increasing competitive pressure driven by institutional expansion, international accreditation standards, and rapid digital transformation. In this context, higher education institutions are required to improve organizational performance through effective governance, high-quality academic services, and professional human resource management (HRM). One important dimension of this transformation is the adoption of electronic human resource management (e-HRM) systems, increasingly integrated with artificial intelligence (AI) to enhance efficiency, objectivity, and data-driven decision-making in HR functions (Jora et al., 2023; Ziakis & Vlachopoulou, 2023). AI-based HRM is now utilized in recruitment screening, performance appraisal, workload analysis, and competency development, positioning digital HR governance as a strategic asset for institutional competitiveness.

Despite its strategic potential, the implementation of AI-based HRM in universities presents a fundamental paradox. On the one hand, AI systems can reduce administrative workload, improve transparency, and accelerate HR processes (Oh et al., 2025). On the other hand, automation may raise concerns about job security, role ambiguity, loss of autonomy, and increased demands for adaptation. Studies indicate that technological transformation often produces ambivalent employee responses, depending on how technology is introduced, supported, and perceived (Saeed et al., 2019; Weber & Kassab, 2024). In academic environments characterized by complex bureaucratic structures and multidimensional responsibilities (teaching, research, and community service), this ambivalence becomes particularly salient.

One critical organizational outcome potentially affected by digital transformation is employee engagement. Engagement reflects employees' vigor, dedication, and absorption in their work and is closely associated with performance, innovation, and institutional sustainability (Okunhon & Ige-Olaobaju, 2024). Conversely, when technological change is perceived as threatening or unsupported, reciprocal responses may manifest as resistance or disengagement (Putra et al., 2026). Within this exchange framework, employees' perceptions of AI constitute a central psychological mechanism linking organizational practices to engagement outcomes.

Although prior studies have examined e-HRM effectiveness and AI adoption in corporate or industrial settings, limited research has explored the psychological mechanisms underlying AI implementation in higher education institutions (Lukman et al., 2024). Existing literature tends to emphasize technological efficiency and system performance rather than employees' perceptions of AI as a threat or an opportunity in academic contexts (Jin et al., 2024; Sharma et al., 2025). Addressing this gap, the present study investigates the influence of AI-based HRM and organizational support on employee engagement, with AI perception positioned as a mediating variable (Shouran & Ali, 2024). By integrating SET with perspectives from technology acceptance and work resource frameworks, this research offers a more comprehensive explanation of how digital HR transformation shapes employee attitudes in higher education. The study contributes theoretically by clarifying the psychological pathway through which AI implementation affects engagement and practically by emphasizing the importance of human-centered digital transformation strategies in universities.

LITERATURE REVIEW

Social Exchange Theory (SET) as the Grand Theoretical Foundation

This study adopts Social Exchange Theory (SET) as the grand theoretical framework to explain employee responses to AI-based HRM implementation. SET posits that relationships between employees and organizations are governed by reciprocal exchanges of resources and socio-emotional benefits (Saeed et al., 2019; Weibel et al., 2025). TAM explains how employees cognitively evaluate AI systems in terms of perceived usefulness and perceived ease of use (Ali et al., 2022; Sharma et al., 2025). JD-R theory explains how organizational and technological factors function as either job resources that enhance motivation or job demands that increase strain (Okunhon & Ige-Olaobaju, 2024; Xie et al., 2022). Therefore, SET provides the overarching reciprocity logic; TAM explains the cognitive evaluation of AI; and JD-R explains how these evaluations translate into engagement outcomes.

AI-Based HRM in Digital Human Resource Governance

AI-based HRM refers to the application of artificial intelligence technologies in HR functions, including automated recruitment screening, performance evaluation, predictive analytics, and competency development systems (Jia et al., 2024; Ziakis & Vlachopoulou, 2023). From the technology-driven HRM perspective (Ismail et al., 2017), AI enhances objectivity, transparency, and efficiency in HR decision-making. However, TAM suggests that technology acceptance depends on employees' perceptions of usefulness and ease of use (Ali et al., 2022). AI can function as a job resource when it enhances work effectiveness and autonomy, but it may become a job demand when it increases monitoring pressure or adaptation strain (Okunhon & Ige-Olaobaju, 2024). Thus, the impact of AI-based HRM on engagement depends not only on technological sophistication but also on employee interpretation and contextual support.

Organizational Support in the Digital Context

Perceived organizational support reflects employees' beliefs that the organization values their contributions and cares about their well-being (Odeibat, 2023). In AI-driven HR transformation, organizational support manifests through training programs, mentoring, transparent communication, and adequate technological infrastructure (Alexiev et al., 2020). According to SET, organizational support strengthens reciprocal relationships because employees feel valued and protected during technological change (Saeed et al., 2019). TAM further explains that training and communication enhance perceived ease of use and usefulness of AI systems, thereby fostering positive perceptions of AI (Sharma et al., 2025).

AI Perception as a Mediating Psychological Mechanism

AI perception refers to employees' evaluation of AI as either an opportunity or a threat. Drawing on TAM, positive perception emerges when employees believe AI enhances performance and is manageable (Ali et al., 2022). The Threat–Opportunity framework suggests that technological interpretation shapes emotional and behavioral responses (Huang & Liu, 2025).

Employee Engagement through the JD-R Lens

Employee Engagement is characterized by vigor, dedication, and absorption (Xie et al., 2022). JD-R theory explains that engagement arises when job resources exceed job demands. Organizational support and well-designed AI systems can act as motivational resources that foster energy and involvement (Jora et al., 2023). Conversely, poorly implemented AI may increase strain and reduce engagement. Thus, engagement in digital environments depends on how technological and organizational factors are interpreted and integrated into employees' work experiences.

Hypotheses Development

AI-Based HRM and Employee Engagement

Previous studies demonstrate that digital HRM systems contribute positively to employee attitudes when they enhance fairness, transparency, and administrative efficiency. Jora et al. (2023) report that technology-enabled HR practices improve work effectiveness and employee responsiveness in digitally transforming organizations. Similarly, Ziakis and Vlachopoulou (2023) argue that AI integration into HR processes increases procedural objectivity and data-driven decision-making, thereby strengthening employees' trust in organizational systems. Furthermore, JD-R theory suggests that technological tools can function as job resources when they enhance autonomy, competence, and efficiency (Okunhon & Ige-Olaobaju, 2024). In this sense, AI-based HRM reduces job demands and strengthens motivational resources, thereby increasing vigor and absorption at work. Therefore, effective implementation of AI-based HRM is expected to foster employee engagement directly. Based on theoretical reasoning and empirical evidence, the following hypothesis is proposed:

H1: AI-based HRM has a positive effect on employee engagement.

Organizational Support and Employee Engagement

Previous empirical studies consistently demonstrate that perceived organizational support plays a crucial role in fostering employee engagement. Saeed et al. (2019) show that when employees perceive strong institutional backing, they are more likely to demonstrate commitment and proactive work behavior. Similarly, Shahzad et al. (2023) find that organizational support during technological transformation enhances employee adaptability and positive work attitudes. Furthermore, according to JD-R theory, organizational support functions as a contextual job resource that enhances motivation and buffers potential job demands arising from digital transformation (Xie et al., 2022). In environments where AI and digital systems may generate adaptation stress, support mechanisms mitigate strain and reinforce vigor, dedication, and absorption. The following hypothesis is proposed:

H2: Organizational support has a positive effect on employee engagement.

AI Perception and Employee Engagement

Previous studies indicate that employees' perceptions of technology significantly influence their work attitudes and behavioral outcomes. Huang and Liu (2025) demonstrate that positive evaluations of AI systems are associated with higher acceptance and stronger work-related motivation. Similarly, Sharma et al. (2025) find that when individuals perceive algorithmic systems as useful and transparent, they are more likely to develop favorable psychological responses toward organizational change.

From the TAM perspective, employees form attitudes toward AI based on perceived usefulness and perceived ease of use (Ali et al., 2022). Furthermore, according to JD-R theory, perception determines whether technology functions as a job resource or job demand (Okunhon & Ige-Olaobaju, 2024). When AI is perceived as an opportunity that improves efficiency and professional development, it becomes a motivational resource that enhances vigor, dedication, and absorption (Setini & Juliasa, 2026). Based on empirical evidence and integrated theoretical reasoning, the following hypothesis is proposed:

H3: AI perception has a positive effect on employee engagement.

AI-Based HRM and AI Perception

Prior studies indicate that the characteristics of technological systems significantly shape users' perceptions of their usefulness and acceptability. [Ali et al. \(2022\)](#) emphasize that system transparency and functional clarity enhance perceived usefulness and ease of use, which are central determinants of positive technology perception. Similarly, [Ziakis and Vlachopoulou \(2023\)](#) argue that AI integration in HR processes strengthens employees' evaluations of fairness and procedural objectivity when supported by clear algorithmic criteria. From the TAM perspective, the structural design and operational performance of AI systems directly influence perceived usefulness and perceived ease of use, which, in turn, shape overall technological perception ([Ali et al., 2022](#); [Sharma et al., 2025](#)). Therefore, effective implementation of AI-based HRM is expected to shape employees' positive perceptions of AI.

H4: AI-based HRM has a positive effect on AI perception.

Organizational Support and AI Perception

Previous research indicates that organizational support plays a significant role in shaping employees' evaluations of technological systems. [Sharma et al. \(2025\)](#) demonstrate that institutional guidance and transparent communication enhance individuals' acceptance of algorithm-based systems. Similarly, [Odeibat \(2023\)](#) highlights that supportive managerial practices during digital transformation reduce uncertainty and strengthen employees' confidence in technological adoption. These mechanisms reduce ambiguity and cognitive resistance, thereby fostering favorable AI perception ([Ali et al., 2022](#)).

H5: Organizational support has a positive effect on AI perception.

The Mediating Role of AI Perception

While AI-based HRM and organizational support may directly influence employee engagement, their effects are unlikely to occur automatically. Prior research suggests that technological and organizational initiatives first undergo cognitive evaluation before influencing attitudinal outcomes ([Ali et al., 2022](#); [Sharma et al., 2025](#)). Employees interpret digital transformation through subjective perception, which determines whether technology is viewed as beneficial or threatening. Therefore, perception becomes a crucial psychological mechanism linking organizational practices to engagement.

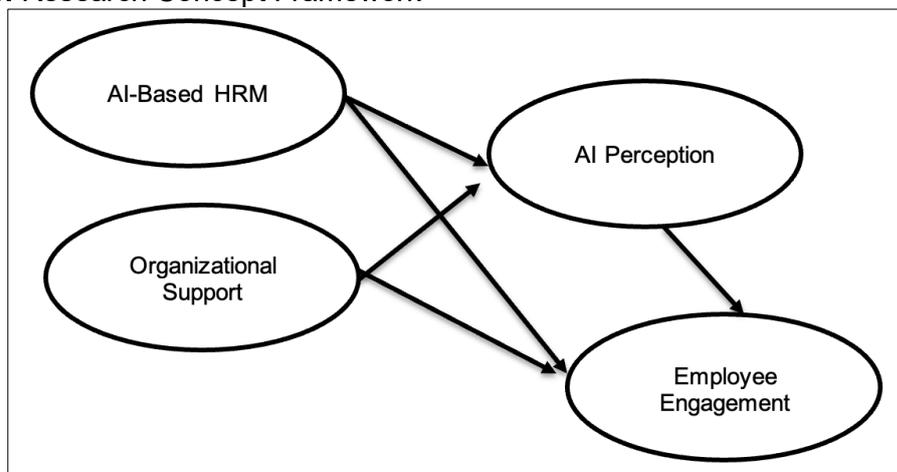
From the perspective of SET, employees reciprocate organizational treatment based on their interpretation of its value and fairness ([Saeed et al., 2019](#)). The TAM further explains that perceived usefulness and ease of use shape employees' overall evaluation of AI systems ([Ali et al., 2022](#)). Thus, both structural (AI-based HRM) and contextual (organizational support) factors shape perceptions of AI before influencing engagement. Additionally, JD-R theory clarifies the motivational mechanism underlying this mediation. AI perception determines whether AI functions as a job resource or a job demand ([Okunhon & Ige-Olaobaju, 2024](#)).

H6: AI perception mediates the relationship between AI-based HRM and employee engagement.

H7: AI perception mediates the relationship between organizational support and employee engagement.

Conceptual Framework

Figure 1. Research Concept Framework



The conceptual framework in [Figure 1](#) positions AI-Based HRM (X1) and Organizational Support (X2) as exogenous variables influencing AI Perception (X3), which subsequently affects Employee Engagement (Y). Grounded in SET, supported by TAM and JD-R theory, the model explains that technological and organizational resources influence engagement through employees' cognitive and motivational processes. AI perception functions as the central psychological bridge translating digital HR practices into reciprocal engagement outcomes within higher education institutions.

RESEARCH METHOD

Research Design

This study adopts a quantitative approach with an explanatory research design to investigate the relationships among AI-based HRM, organizational support, AI perception, and employee engagement. An explanatory design allows the examination of both direct and mediating relationships within a structural model. The analysis employs Partial Least Squares–Structural Equation Modeling (PLS-SEM), which is suitable for predictive analysis, mediation testing, and the estimation of complex models involving latent constructs ([Hair et al., 2021](#)). This method is particularly appropriate for research in emerging contexts, such as AI implementation in higher education.

Population and Sampling

The population comprises lecturers and education staff at universities in Bali Province, Indonesia, who have implemented e-HRM systems integrated with AI-based HR applications. At the time of data collection, 12 public and private universities in Bali had adopted digital HR systems supporting functions such as e-recruitment, performance monitoring, and workload management. Purposive sampling was applied to select respondents who met the following criteria: (1) employed for at least one year, (2) actively using the e-HRM or AI-based HR system, and (3) willing to participate voluntarily. Sample size determination used statistical power analysis through G*Power 3.1 rather than the traditional “10-times rule” ([Hair et al., 2021](#)). With three predictors, a medium effect size ($f^2 = 0.15$), significance level ($\alpha = 0.05$), and statistical power ($1 - \beta = 0.80$), the minimum required sample size was 77 respondents. A total of 250 valid responses were collected, exceeding the minimum requirement and ensuring adequate statistical power.

Data Collection Procedure

Data were collected through an online questionnaire distributed between January and March 2025 via institutional communication channels. The questionnaire included two sections: respondent demographics and measurement items for the research variables, using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Measurement items were adapted from validated scales in prior studies. Content validity was evaluated through expert judgment involving two senior lecturers in HRM and educational technology. A pilot test with 30 respondents was conducted to assess clarity and reliability, yielding minor revisions to several items.

Ethical Considerations

This study received ethical approval from the Institutional Research Ethics Committee of Warmadewa University (Approval No: [insert number]). Participation was voluntary, and informed consent was obtained from all respondents. No personally identifiable information was collected, and all data were analyzed anonymously and used solely for academic purposes.

Operational Definitions of Variables

AI-Based HRM (X1) refers to the implementation of artificial intelligence technologies in HR functions, including automated recruitment, algorithm-based performance appraisal, workload monitoring, and competency development systems (Jia et al., 2024; Ziakis & Vlachopoulou, 2023). Organizational Support (X2) reflects employees' perceptions of the extent to which the institution provides training, technological infrastructure, mentoring, and transparent communication during digital transformation (Odeibat, 2023). AI Perception (X3) denotes employees' cognitive and affective evaluation of AI as either an opportunity to enhance performance or a threat that increases workload and reduces autonomy (Ali et al., 2022). Employee Engagement (Y) refers to a positive, fulfilling work-related state characterized by vigor, dedication, and absorption (Xie et al., 2022).

All constructs were operationalized reflectively, and their indicators are presented in Table 1, including construct definitions, measurement items, and literature sources.

Table 1. Table of Variables, Indicators, and Sources

Variable	Indicators	Code	Variable Sources
AI-Based HRM (X1)	AI systems help the recruitment and selection process	X1.1	Ismail (2017), Odeibat (2023)
	Performance appraisal is carried out through an objective algorithm	X1.2	
	AI makes administrative tasks easier	X1.3	
	AI provides competency development recommendations	X1.4	
	AI improves the efficiency and speed of HR services	X1.5	
Organizational Support (X2)	The organization provides technology use training	X2.1	Aldossari et al. (2023), Sharma et al. (2025)
	There is technical assistance for system users	X2.2	
	Leaders provide clear communication about the application of AI	X2.3	
	Digital facilities and infrastructure are adequately provided	X2.4	
	Organizations care about the difficulty of technology adaptation	X2.5	
	AI makes my job easier	X3.1	

AI Perception (X3 – Mediator)	AI improves work effectiveness and quality	X3.2	Liu et al. (2023), Sarala et al. (2025)
	AI does not threaten my job role	X3.3	
	AI provides opportunities for self-development	X3.4	
	Overall, AI provides more opportunities than threats	X3.5	
Employee Engagement (Y)	I feel energized while working (vigor)	Y1	Sabihaini et al. (2024), Setyaningrum et al. (2023)
	I am enthusiastic about my work (dedication)	Y2	
	I feel immersed in work (absorption)	Y3	
	I have a strong commitment to work	Y4	
	I want to continue to contribute to the institution	Y5	

Data Analysis

This study employed PLS-SEM with SmartPLS 4. PLS-SEM was selected because the research aims to examine predictive relationships and mediation effects within a relatively complex structural model involving multiple latent constructs (Hair et al., 2021). In addition, PLS-SEM is appropriate for exploratory and prediction-oriented research in emerging fields such as AI-based HRM in higher education. The data analysis was conducted in two main stages: evaluation of the measurement model (outer model) and evaluation of the structural model (inner model).

In the measurement model assessment, convergent validity was evaluated using factor loadings (>0.70) and Average Variance Extracted ($AVE > 0.50$). Internal consistency reliability was assessed using Cronbach's Alpha and Composite Reliability ($CR > 0.70$). Discriminant validity was examined using the Heterotrait–Monotrait ratio ($HTMT < 0.90$). Additionally, multicollinearity among indicators was assessed using the Variance Inflation Factor ($VIF < 5.00$) to ensure that collinearity did not distort parameter estimates.

In the structural model evaluation, the coefficient of determination (R^2) was used to assess the explanatory power of endogenous constructs. Effect size (f^2) was examined to assess the substantive impact of each exogenous variable on the endogenous variables, using the criteria of small (0.02), medium (0.15), and large (0.35). Predictive relevance was evaluated using the blindfolding procedure, yielding Q^2 values (>0 indicating predictive relevance). Model fit was assessed using the Standardized Root Mean Square Residual ($SRMR < 0.08$) as recommended in recent PLS-SEM guidelines (Hair et al., 2021).

Before model estimation, preliminary data screening was conducted, including checks for missing values, outliers, and response consistency. Harman's single-factor test was conducted to assess potential common-method bias, ensuring that no single factor accounted for the majority of variance. To assess potential common method bias arising from self-reported questionnaire data, Harman's single-factor test was conducted via exploratory factor analysis with unrotated principal component extraction. All measurement items from the constructs of AI-based HRM, organizational support, AI perception, and employee engagement were entered simultaneously into the analysis. The results indicate that the first factor explained 38.47% of the total variance, which is below the recommended threshold of 50% (Podsakoff et al., 2003). This finding suggests that no single factor dominates the variance among the measurement items. Therefore, common method bias is not considered a serious issue in this study.

Research Procedure

The research procedure began with problem identification and the development of a theoretical model based on the SET, the Technology Acceptance Model (TAM), and Job Demands–Resources (JD–R) Theory. A conceptual framework and research hypotheses were subsequently formulated. Measurement instruments were adapted from validated scales used in prior studies, and content validity was assessed through expert review by senior academics in HRM and digital transformation. A pilot test with 30 respondents was conducted to assess item clarity and preliminary reliability. Data were collected online through institutional networks between January and March 2025. Only respondents meeting the inclusion criteria were included in the study. After collection, responses were screened, coded, and cleaned before being analyzed using SmartPLS 4 to evaluate the measurement and structural models and to test the proposed hypotheses. The study followed ethical research standards. Participants received informed consent explaining the research objectives, voluntary participation, confidentiality, and the right to withdraw. No personally identifiable information was collected, and all data were analyzed anonymously. Ethical approval was obtained from the Institutional Research Ethics Committee of Warmadewa University.

RESULTS

Respondents' Profile

Table 2. Respondent Profiles

	Criteria	Quantity (n)	Percentage (%)
Data Description	Distributed Questionnaire	250	100
	Questionnaire Back	250	100
	Valid Questionnaire	250	100
Gender	Man	110	44
	Woman	140	56
Respondent Age	< 30 years old	40	16
	31–40 years	105	42
	41–50 years	70	28
	> 50 years	35	14
Long Time Working	1–3 years	45	18
	4–7 years	90	36
	8–10 years	60	24
	> 10 years	55	22
Job Title/ Position	Lecturer	160	64
	Education Personnel	60	24
	Academic Administration	20	8
	Managerial / Coordinator	10	4
Frequency of Use of e-HRM/AI	Every day	95	38
	2–3 times per week	85	34
	1 time per week	40	16
	Infrequently	30	12

Table 2 shows that all 250 distributed questionnaires were returned and deemed valid for analysis, indicating a high level of participation among lecturers and education staff in universities implementing e-HRM and AI-based technologies. Female respondents slightly outnumbered male respondents (56%), reflecting the general composition of academic staff in Indonesian universities. The largest age group was 31–40 years (42%), representing productive-age employees actively engaged with digital technologies. Most respondents had 4–7 years of work experience (36%), suggesting adequate familiarity with digital HR systems and AI-based policies. In terms of position, lecturers constituted the majority of respondents (64%), followed by education staff (24%), both of whom

frequently interact with the e-HRM system. Furthermore, 72% of respondents reported using the e-HRM and AI system at least twice a week, indicating substantial direct experience relevant to the analysis of AI perception in this study.

Table 3. Outer Model – Integrated

Variable	Indicators	Loading Factor	AVE	Cronbach's Alpha	Composite Reliability	HTMT (Range)
AI-Based HRM (X1)	X1.1	0.812	0.701	0.889	0.918	0.764 – 0.801
	X1.2	0.847				
	X1.3	0.835				
	X1.4	0.802				
	X1.5	0.861				
Organizational Support (X2)	X2.1	0.821	0.709	0.901	0.928	0.764 – 0.788
	X2.2	0.854				
	X2.3	0.876				
	X2.4	0.804				
	X2.5	0.828				
AI Perception (X3)	X3.1	0.803	0.731	0.912	0.936	0.788 – 0.812
	X3.2	0.847				
	X3.3	0.812				
	X3.4	0.869				
	X3.5	0.885				
Employee Engagement (Y)	Y1	0.824	0.720	0.895	0.925	0.722 – 0.812
	Y2	0.873				
	Y3	0.858				
	Y4	0.810				
	Y5	0.865				

The test results in [Table 3](#) indicate that the outer model shows that all indicators in this study meet the quality criteria of the PLS-SEM instrument. The loading factor for each indicator exceeds 0.70, indicating that all indicators represent a well-measured construct. The AVE value for all variables also exceeded the threshold of 0.50, so convergent validity has been met. Furthermore, discriminant validity was assessed using the HTMT value, which showed that all values were below 0.90, indicating that each construct is distinct and there is no overlap among variables. In terms of reliability, Cronbach's Alpha and Composite Reliability values for the entire construct were above 0.70, which indicates the internal consistency of the instrument is excellent. Overall, the research instrument is deemed valid and reliable and therefore suitable for internal model analysis.

Inner Model Analysis (Structural Model)

Evaluation of the Inner Model

Table 4. R² and Q² values

Endogenous Variable	R ²	Category	Q ²
AI Perception (X3)	0.482	Moderate	0.317
Employee Engagement (Y)	0.569	Moderate – Strong	0.368

The R² value in [Table 4](#) shows that AI-based HRM and organizational support are able to explain 48.2% of the variation in AI perception, while all variables in the model explain 56.9% of the variation in employee engagement. A Q² value > 0 indicates that the model has good predictive relevance.

Table 5. Effect Size (f²)

Relationship	f ²	Category
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AI-Based HRM → AI Perception	0.182	Medium
Organizational Support → AI Perception	0.214	Medium
AI-Based HRM → Employee Engagement	0.091	Small
Organizational Support → Employee Engagement	0.128	Small
AI Perception → Employee Engagement	0.267	Medium

Effect size (f^2) is used to see the magnitude of the contribution of each exogenous variable to the endogenous variable in the model. According to Chin (1998), f^2 values of 0.02, 0.15, and 0.35 are classified as small, medium, and large, respectively. The results in Table 5 showed that AI-based HRM and organizational support had a moderate influence on AI perception, while the direct influence of both on employee engagement was relatively small. In contrast, AI perception has the strongest effect size on employee engagement, confirming its role as a key factor that bridges the influence of technology and organizational support on employee work engagement.

Table 6. Hypothesis Testing Results

	Hypothesis	Coefficient (β)	T-Statistics	P-Value	Result
H1	AI-Based HRM → Employee Engagement	0.231	4.086	0.000	Accepted
H2	Organizational Support → Employee Engagement	0.264	4.751	0.000	Accepted
H3	AI Perception → Employee Engagement	0.419	7.893	0.000	Accepted
H4	AI-Based HRM → AI Perception	0.401	7.214	0.000	Accepted
H5	Organizational Support → AI Perception	0.438	8.102	0.000	Accepted
H6	AI-Based HRM → AI Perception → Employee Engagement	0.168	5.921	0.000	Accepted (Partial Mediation)
H7	Organizational Support → AI Perception → Employee Engagement	0.183	6.447	0.000	Accepted (Partial Mediation)

Table 6 presents the results of the hypothesis testing, including the standardized coefficients (β), t-statistics, and p-values. The findings indicate that all proposed hypotheses are supported. First, AI-based HRM has a positive and significant effect on employee engagement ($\beta = 0.231$, $t = 4.086$, $p < 0.001$), supporting H1. This result suggests that the implementation of AI-driven HRM practices contributes to higher levels of employee engagement within the organization.

Second, organizational support also demonstrates a positive and significant effect on employee engagement ($\beta = 0.264$, $t = 4.751$, $p < 0.001$), confirming H2. This finding indicates that employees who perceive greater organizational support exhibit greater work engagement.

Third, AI perception shows the strongest direct effect on employee engagement ($\beta = 0.419$, $t = 7.893$, $p < 0.001$), supporting H3. This result implies that employees' positive perceptions of AI technologies play a crucial role in enhancing their engagement levels.

Regarding the relationships with the mediating variable, AI-based HRM significantly influences AI perception ($\beta = 0.401$, $t = 7.214$, $p < 0.001$), supporting H4. Similarly, organizational support has a positive and significant effect on AI perception ($\beta = 0.438$, $t = 8.102$, $p < 0.001$), confirming H5. These findings suggest that both AI-based HRM

practices and organizational support shape employees' perceptions of AI in the workplace.

Furthermore, the mediation analysis indicates that AI perception partially mediates the relationship between AI-based HRM and employee engagement ($\beta = 0.168$, $t = 5.921$, $p < 0.001$), supporting H6. Likewise, AI perception partially mediates the relationship between organizational support and employee engagement ($\beta = 0.183$, $t = 6.447$, $p < 0.001$), supporting H7. These results demonstrate that positive perceptions of AI serve as an important mechanism through which AI-based HRM practices and organizational support enhance employee engagement.

DISCUSSION

This study examined how AI-based HRM and organizational support influence employee engagement, with AI perception functioning as a mediating mechanism. While the results generally support the proposed hypotheses, a deeper analysis reveals several important theoretical insights that extend beyond confirmatory findings.

The Relative Influence of AI-Based HRM and Organizational Support on Engagement

The findings confirm that both AI-based HRM and organizational support positively influence employee engagement. However, a closer examination of the structural coefficients reveals an important nuance. While AI-based HRM has a significant direct effect, its influence is comparatively weaker than the effect of AI perception on engagement. This suggests that technological implementation alone is insufficient to maximize engagement outcomes. Instead, employees' interpretations of AI systems play a more decisive role.

This finding extends prior research that emphasizes the operational benefits of digital HR systems (Jora et al., 2023; Ziakis & Vlachopoulou, 2023) by demonstrating that structural technological improvements do not automatically translate into stronger engagement. In the context of higher education, where professional autonomy and academic identity are highly valued, the psychological interpretation of AI appears to outweigh the system's technical sophistication. Thus, digital HR transformation should not be evaluated solely in terms of efficiency gains but also in terms of its perceived meaning among employees.

From a SET perspective, AI-based HRM represents an organizational investment. However, reciprocity is activated only when employees interpret this investment positively. This reinforces the argument that technology must be embedded within relational and perceptual dynamics rather than treated as a purely structural innovation.

AI Implementation is Not the Strongest Driver of Engagement

Although AI-based HRM has a significant direct effect on employee engagement, its coefficient is weaker than that of AI perception. This suggests that technological implementation alone does not automatically generate high engagement. In other words, structural digital transformation is insufficient without a positive psychological interpretation.

These findings challenge technology-centric perspectives that assume efficiency and automation directly enhance work motivation. While previous research emphasizes the operational benefits of AI in HR systems (Jia et al., 2024; Ziakis & Vlachopoulou, 2023), the present study demonstrates that the motivational impact of AI depends largely on how employees interpret it. In higher education institutions, where professional

autonomy and academic identity are highly valued, employees may be more sensitive to the perceived implications of AI than to its technical functionality, even when that value is not activated.

AI Perception as the Central Psychological Mechanism

One of the most important findings is that AI perception exerts the strongest direct influence on employee engagement among all predictors. This indicates that perception functions as a central motivational driver rather than merely a mediating variable.

From the TAM perspective, employees evaluate AI based on perceived usefulness and ease of use (Ali et al., 2022; Setini & Juliasa, 2026). However, this study extends TAM by showing that perception not only influences acceptance intention but also deeper motivational states such as vigor and dedication. This aligns with JD-R theory, which posits that work engagement emerges when employees experience adequate job resources. AI perception determines whether AI is cognitively framed as a resource (enhancing efficiency and fairness) or as a demand (increasing monitoring and pressure).

Organizational Support: Direct and Indirect Influence

The findings also indicate that organizational support significantly affects employee engagement, both directly and indirectly, through perceptions of AI. Notably, the indirect pathway through perception represents a substantial portion of its total effect. This suggests that organizational support plays a dual role. First, it functions as a direct socio-emotional resource, consistent with SET (Saeed et al., 2019). When employees feel supported during technological change, they reciprocate with stronger engagement. Second, organizational support shapes how AI is interpreted. Training, mentoring, and transparent communication reduce uncertainty and foster positive perceptions of AI.

Interestingly, the mediation results suggest that organizational support may exert a stronger psychological influence than AI-based HRM. Employees appear more responsive to relational and contextual support than to technological features alone. This finding reinforces the argument that digital transformation in universities is fundamentally human-centered.

The mediation analysis reveals partial rather than full mediation. This indicates that AI-based HRM and organizational support retain direct effects on engagement even after accounting for perception. Theoretically, this suggests that reciprocity (SET) operates through both cognitive evaluation and direct socio-emotional exchange. While perception is a key mechanism, structural and relational factors independently contribute to engagement. For example, transparent AI systems may enhance engagement through procedural fairness even if perception is not strongly emotional. Likewise, organizational support may directly increase commitment regardless of technological interpretation. Thus, engagement in digital environments is multi-determined rather than purely perception-driven.

Boundary Conditions and Alternative Explanations

Several boundary conditions should be acknowledged. First, this study was conducted in universities within Bali, Indonesia. Cultural characteristics such as collectivism and high power distance may strengthen reciprocity dynamics, thereby amplifying the influence of organizational support. In more individualistic settings, perception of autonomy loss might play a stronger role.

Second, employees' digital literacy levels may influence perceptions of AI independently of organizational initiatives. Employees with higher technological competence may

naturally interpret AI more positively. Future research should examine moderating variables such as digital readiness, technostress, or leadership style. Third, the rapid stage of digital transformation in higher education may create novelty effects, in which positive engagement reflects enthusiasm for adaptation rather than long-term stability. Longitudinal studies would be valuable to assess the sustainability of these relationships.

Theoretical Contributions

First, it advances SET by demonstrating that cognitive appraisal mechanisms mediate reciprocity in digital transformation contexts. Organizational investments in AI influence engagement primarily when interpreted positively.

Second, it extends the TAM beyond behavioral intention by demonstrating its relevance for explaining motivational outcomes, such as engagement. Third, it integrates JD-R theory into AI-based HRM research by empirically demonstrating that technological systems function as job resources only when positively perceived. Overall, the findings indicate that AI perception functions more strongly than direct technological implementation, and organizational support exerts both direct and indirect psychological influence. Therefore, the success of AI-based HRM in higher education depends less on technological sophistication and more on how institutions construct supportive and meaningful digital environments.

CONCLUSION

This study examines the influence of AI-based HRM and organizational support on employee engagement with AI perception as a mediating variable in universities implementing AI-based e-HRM systems. The PLS-SEM results indicate that all tested relationships are positive and significant. AI-based HRM contributes to higher employee engagement by supporting administrative efficiency and data-driven HR processes. Organizational support, such as training, mentoring, and clear communication regarding AI implementation, also strengthens employee engagement.

AI perception plays a crucial role both as a direct predictor of engagement and as a mediating mechanism. When employees perceive AI as an opportunity rather than a threat, the positive effects of AI-based HRM and organizational support on engagement become stronger. These findings highlight that successful HR digital transformation depends not only on technological capability but also on employee perceptions and institutional support. The results reinforce the relevance of SET, TAM, and JD–R Theory in explaining employee behavior in digital HR environments.

Universities should adopt a human-centered approach to AI implementation by promoting transparency, communication, and employee involvement in digital transformation processes. Institutions are also encouraged to strengthen organizational support through ongoing training and technical assistance to foster positive perceptions of AI and sustain employee engagement. Additionally, AI perception can serve as a strategic indicator for evaluating the success of HR digital transformation.

LIMITATION

This study has several limitations. First, the research context is limited to universities in Bali, which may restrict generalizability to other regions or institutional settings. Second, the cross-sectional design limits the ability to observe changes in perceptions and engagement over time. Third, the use of self-reported data may introduce potential bias. Future studies are encouraged to incorporate longitudinal designs and multi-source data to strengthen the robustness of findings.

Future studies should broaden the research context to include other sectors, such as industry, banking, and public organizations, to improve generalizability. Additional variables such as digital readiness, technostress, trust in AI, and leadership style may also be examined as mediators or moderators. Employing mixed-method approaches could further enrich the understanding of employees' experiences with AI-based HRM.

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DECLARATION OF CONFLICTING INTEREST

The authors declare that there are no conflicts of interest related to this publication.

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ABOUT THE AUTHOR(S)

1st Author

Ida Bagus Udayana Putra is a lecturer and researcher in management and organizational studies. His research interests include HRM, leadership, organizational behaviour, digital transformation, and sustainable business performance. He has published in various international journals on topics such as organizational agility, employee performance, emotional labor, and mediation analysis in management research. His work emphasizes practical and data-driven approaches to improving organizational effectiveness and sustainability in emerging economies.

Email: udayana10@gmail.com

ORCID ID: <https://orcid.org/0000-0002-4375-916X>

2nd Author

Made Setini is a lecturer and researcher in management and business studies in Indonesia. Her research interests include HRM, digital transformation, sustainable business strategy, green leadership, SME development, and innovation behavior. She has published extensively in international and national journals on topics such as AI integration in marketing, green products, corporate entrepreneurship, customer satisfaction, and sustainable performance. Her work emphasizes the role of leadership, digital strategy, and environmental sustainability in enhancing organizational competitiveness and long-term growth in emerging economies.

Email: setini@warmadewa.ac.id

ORCID ID: <https://orcid.org/0000-0002-7748-823>

3rd Author

Ida Bagus Nyoman Udayana is a lecturer and researcher in the field of management and marketing. His research interests focus on digital marketing, electronic word of mouth (e-WOM), consumer behavior, brand trust, customer satisfaction, and sustainable leadership. He has published extensively in national and international journals on topics such as social media marketing, purchase intention, customer loyalty, green performance, and sustainability-oriented leadership. His work emphasizes the integration of digital platforms, customer experience, and strategic management approaches to enhance organizational competitiveness and long-term sustainability.

Email: ibn.udayana@yahoo.co.id

ORCID ID: <https://orcid.org/0000-0002-9819-1970>

4th Author

Mochamad Soelton is a lecturer and researcher specializing in HRM and organizational behavior. His research interests include sustainable employee performance, green

HRM, servant leadership, organizational citizenship behavior, turnover intention, energy efficiency, and corporate social responsibility. He has published extensively in national and international journals on topics related to sustainable management, environmental awareness, workplace stress, cyberloafing, and organizational performance. His scholarly work emphasizes the integration of sustainability principles, leadership approaches, and employee behavioral dynamics to enhance organizational effectiveness in contemporary business environments.

Email: soelton@mercubuana.ac.id

ORCID ID: <https://orcid.org/0000-0003-1055-4085>

5th Author

Olivia Imaculada do Rêgo Sarmiento is a postgraduate student actively engaged in academic research. Her interests focus on management studies, organizational behavior, and contemporary business issues. She actively participates in research projects and academic collaborations, contributing to scholarly discussions through empirical studies and academic publications. Her work emphasizes the application of theoretical frameworks to practical organizational and business contexts.

Email: olivia_sarmiento@yahoo.com

ORCID ID: <https://orcid.org/0000-0002-7748-8xx>