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Artificial Intelligence-Driven Human Resource Management and Employee Satisfaction: The Mediating Role of Employee Engagement

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Abstract
Organisations increasingly use artificial intelligence (AI) in recruitment, performance management, employee learning and workplace support. This study examines the relationship between AI-driven human resource management (AI-HRM) and employee satisfaction, with particular attention to the mediating role of employee engagement. Data were collected using a structured questionnaire comprising eight items on AI-HRM, nine items on work engagement and six items on employee satisfaction. The study analysed responses from 112 respondents. The reliability analysis indicated acceptable internal consistency, with Cronbach's alpha values of 0.71 for AI-HRM, 0.77 for employee engagement and 0.77 for employee satisfaction. Regression-based mediation analysis using 5,000 bootstrap samples showed a positive association between AI-HRM and employee engagement ($b = 0.331$, $p = .004$). Employee engagement was also positively associated with employee satisfaction ($b = 0.342$, $p < .001$). However, the total effect of AI-HRM on employee satisfaction was not statistically significant ($b = 0.195$, $p = .093$). The indirect effect through employee engagement was 0.113, with a 95% confidence interval of [0.032, 0.220], whereas the direct effect was not statistically significant ($b = 0.082$, $p = .472$). These findings suggest that employee engagement may help explain the relationship between AI-HRM and employee satisfaction. Further research using appropriate research designs and diverse employee samples is needed to assess the generalisability of these findings.
Keywords: AI-driven HRM, employee engagement, employee satisfaction, mediation, employee survey.

1. Introduction

Artificial intelligence (AI) is becoming an increasingly important part of human resource management (HRM), with applications in recruitment, employee performance evaluation, predictive attrition analysis and personalised learning (Davenport & Ronanki, 2018; Tambe et al., 2019). These technologies enable organisations to process employee-related information, support managerial decisions and streamline routine HR activities. However, the adoption of AI in HRM also raises questions about how technology-driven practices influence employees' workplace experiences and attitudes.

Previous research on AI in HRM has examined its potential to improve organisational efficiency and decision-making, while employee-related outcomes warrant further investigation (Vrontis et al., 2022). In particular, understanding the relationship between AI-driven HRM and employee satisfaction requires attention to the factors that may shape employees' responses to these practices. Employee engagement is one such factor because it reflects employees' level of energy, dedication and involvement in their work. Examining engagement alongside satisfaction may therefore provide a clearer understanding of how AI-enabled HR practices relate to employees' perceptions of their jobs.

Against this background, the present study investigates the relationship between AI-driven human resource management (AI-HRM) and employee satisfaction, focusing on the potential mediating role of employee engagement.

The study addresses four research questions:

(1) Is AI-HRM associated with employee satisfaction?
(2) Is AI-HRM associated with employee engagement?
(3) Is employee engagement associated with employee satisfaction?
(4) Does employee engagement mediate the relationship between AI-HRM and employee satisfaction?

By examining these relationships within a single analytical framework, the study seeks to clarify the proposed connection between AI-HRM, employee engagement and employee satisfaction. It also provides a basis for assessing whether engagement helps explain the relationship between AI-enabled HR practices and employee satisfaction. The findings are intended to contribute to further empirical investigation of employee responses to the growing use of AI in human resource management.

2. Theoretical Background And Hypotheses

The relationship between AI-driven human resource management (AI-HRM), employee engagement and employee satisfaction can be examined through established theories of workplace motivation and employee attitudes. The Job Demands–Resources (JD-R) model, Social Exchange Theory and Affective Events Theory provide complementary perspectives for understanding these relationships.

The Job Demands–Resources model proposes that job resources support employee engagement and contribute to positive work-related outcomes (Bakker & Demerouti, 2007). In the context of AI-HRM, resources such as accessible HR support, timely feedback, personalised learning opportunities and transparent decision-making may help employees perform their duties more effectively. However, these benefits depend on how AI-enabled practices are implemented and perceived by employees. When such practices are useful and supportive, they may be associated with higher levels of engagement.

Social Exchange Theory provides another perspective on the relationship between HR practices and employee behaviour. According to Blau (1964), social exchanges involve reciprocal responses to benefits and support received from others. Employees who perceive their organisation's HR practices as fair and supportive may respond through greater involvement in their work. AI-enabled HR systems may contribute to this perception when employees consider them reliable, transparent and responsive to their needs. Conversely, concerns about fairness, transparency or excessive monitoring may weaken these positive responses.

Affective Events Theory explains how workplace experiences influence employees' emotional responses and job-related attitudes (Weiss & Cropanzano, 1996). HR practices can form part of employees' everyday work experiences, shaping how they evaluate their jobs and working conditions. Consistent and supportive experiences may contribute to favourable job evaluations, whereas frustrating or impersonal interactions may have the opposite effect. This perspective provides a theoretical basis for examining the relationship between AI-HRM and employee satisfaction.

Work engagement is commonly described as a positive, fulfilling work-related state characterised by vigour, dedication and absorption (Schaufeli et al., 2002, 2006). The concept is also connected to Kahn's (1990) account of personal engagement, which emphasises employees' investment of their physical, cognitive and emotional resources in their work roles. Job satisfaction, in contrast, concerns employees' evaluations of their jobs and the extent to which they view their work experiences favourably (Spector, 1985). Although engagement and satisfaction are distinct constructs, both have been associated with important organisational outcomes (Harter et al., 2002).

Building on these theoretical perspectives, the present study examines the relationships between AI-HRM, employee engagement and employee satisfaction. The following hypotheses are proposed.

H1: AI-HRM has a positive relationship with employee satisfaction.

This hypothesis proposes that employees' perceptions of AI-enabled HR practices are positively associated with their evaluations of their jobs. The proposed relationship is informed by Affective Events Theory, which explains how workplace experiences contribute to job-related attitudes (Weiss & Cropanzano, 1996).

H2: AI-HRM has a positive relationship with employee engagement.

Drawing on the JD-R model, this hypothesis proposes that AI-enabled HR practices perceived as useful, fair and supportive may be associated with greater employee engagement by providing resources that facilitate work and employee development (Bakker & Demerouti, 2007).

H3: Employee engagement has a positive relationship with employee satisfaction.

This hypothesis proposes that employees who demonstrate greater vigour, dedication and involvement in their work may also report more favourable evaluations of their jobs. This proposition is consistent with research linking employee engagement and satisfaction to organisational outcomes (Harter et al., 2002).

H4: Employee engagement mediates the relationship between AI-HRM and employee satisfaction.

This hypothesis proposes that employee engagement may help explain the relationship between AI-HRM and employee satisfaction. Drawing on Social Exchange Theory, employees who perceive HR practices as supportive may respond with greater involvement in their work, which may, in turn, be associated with higher job satisfaction (Blau, 1964). The mediation analysis examines whether the relationship between AI-HRM and satisfaction operates indirectly through employee engagement.

3. Methodology

3.1 Research Design and Data Collection

The study adopted a quantitative, cross-sectional research design to examine the relationships between AI-driven human resource management (AI-HRM), employee engagement and employee satisfaction. Data were collected through a structured questionnaire, and the final dataset comprised 112 respondents. The questionnaire captured respondents' perceptions of AI-enabled HR practices, their level of work engagement and their satisfaction with their jobs.

The analysis was designed to examine the relationships among the three constructs and assess whether employee engagement mediates the relationship between AI-HRM and employee satisfaction. The respondent profile was summarised using demographic and employment-related characteristics, including age, gender, educational background, work experience, industry sector and designation.

3.2 Measures

AI-HRM was assessed using eight items covering AI applications in recruitment, performance evaluation, personalised training, HR chatbots, fairness and transparency, speed and accuracy, human oversight, and ease of use. Responses were recorded on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Work engagement was assessed using nine items structured around the dimensions of the Utrecht Work Engagement Scale (UWES-9), associated with Schaufeli et al. (2006). Responses were recorded on a seven-point scale scored from 0 to 6. Employee satisfaction was assessed using six items informed by the job satisfaction measurement literature, including Spector (1985), with responses recorded on a five-point scale ranging from 1 to 5.

Construct scores were calculated as the mean of the relevant items. Because work engagement was measured on a 0–6 scale, whereas AI-HRM and employee satisfaction were measured on 1–5 scales, direct comparisons of their raw mean scores require caution. The questionnaire items and scoring procedures should be documented to support replication of the study.

3.3 Data Analysis

The data analysis examined the measurement properties of the study constructs and the proposed relationships among them. Internal consistency was assessed using Cronbach's alpha, while composite reliability (CR) and average variance extracted (AVE) were used to examine additional aspects of measurement quality. Pearson correlation analysis was conducted to assess the direction and strength of the relationships among AI-HRM, employee engagement and employee satisfaction.

Regression-based mediation analysis, corresponding to PROCESS Model 4 (Hayes, 2018), was used to examine the potential mediating role of employee engagement. The analysis estimated the relationship between AI-HRM and engagement, the relationship between engagement and satisfaction while controlling for AI-HRM, and the total and direct relationships between AI-HRM and satisfaction. The indirect effect was evaluated using 5,000 bootstrap resamples, with a 95% confidence interval used to assess its statistical significance (Preacher & Hayes, 2008).

The analysis also included Harman's single-factor test as an assessment of potential common method bias, following Podsakoff et al. (2003). Statistical analyses were conducted in Python using NumPy and SciPy. The reported results were interpreted in relation to the proposed hypotheses and the limitations of the research design.

4. Results

4.1 Sample Profile

Table 1 presents the demographic and professional characteristics of the 112 respondents included in the analysis. The profile covers age, gender, educational background, work experience, industry sector and professional designation.

Table 1. Demographic and Professional Profile of Respondents (N = 112)

Variable	Category	n	%
Age	18–25 years	33	29.5
	26–35 years	46	41.1
	36–45 years	24	21.4
	46 years and above	9	8.0
Gender	Male	65	58.0
	Female	40	35.7
	Prefer not to say	7	6.3
Education	Graduate	33	29.5
	Postgraduate	76	67.9
	Other	3	2.7
Work experience	Less than 2 years	26	23.2
	2–5 years	43	38.4
	5–10 years	25	22.3
	More than 10 years	18	16.1
Industry sector	IT	37	33.0
	Banking and finance	26	23.2
	Other	19	17.0
	Education	11	9.8
	Manufacturing	7	6.3

	Healthcare	7	6.3
	Retail and services	5	4.5
Designation	Entry-level	31	27.7
	Mid-level	56	50.0
	Senior-level	25	22.3

The largest age group was 26–35 years, representing 41.1% of the sample. Male respondents accounted for 58.0%, while female respondents represented 35.7%. In terms of educational background, postgraduates constituted the largest group (67.9%). Regarding professional experience, 38.4% of respondents reported between two and five years of experience. Participants working in IT formed the largest sector group (33.0%), followed by banking and finance (23.2%). Mid-level professionals represented half of the sample (50.0%).

4.2 Reliability, Validity and Common Method Bias

The reliability and convergent validity assessments are summarised in Table 2. Cronbach's alpha and composite reliability (CR) were examined to assess the internal consistency of the three constructs, while average variance extracted (AVE) was used to evaluate convergent validity.

Table 2. Reliability and Convergent Validity Assessment

Construct	Items	Cronbach's α	CR	AVE
AI-HRM	8	0.71	0.80	0.33
Employee engagement	9	0.77	0.83	0.36
Employee satisfaction	6	0.77	0.84	0.47

Cronbach's alpha values ranged from 0.71 to 0.77, while composite reliability values ranged from 0.80 to 0.84. These results indicate acceptable internal consistency based on the commonly applied threshold of 0.70. However, the AVE values were below the conventional benchmark of 0.50 for all three constructs. AI-HRM recorded an AVE of 0.33, engagement 0.36 and satisfaction 0.47. Although the composite reliability estimates were above 0.70, the AVE results indicate that convergent validity requires further examination. As discussed by Fornell and Larcker (1981), composite reliability may be considered alongside AVE when assessing measurement quality; however, satisfactory reliability alone does not establish convergent validity.

Harman's single-factor test indicated that the first unrotated factor accounted for 20.0% of the total variance. This value was below the commonly used 50% benchmark, suggesting that a single factor did not account for most of the variance in the analysed items. Nevertheless, this test alone cannot establish the absence of common method bias, and its findings should be interpreted with appropriate caution.

4.3 Descriptive Statistics and Correlations

Table 3 reports the means, standard deviations and Pearson correlations for AI-HRM, employee engagement and employee satisfaction. These statistics provide an overview of the observed scores and the direction and strength of the relationships among the study variables.

Table 3. Descriptive Statistics and Correlations Among Study Variables

Variable	M	SD	1	2	3
1. AI-HRM	3.23	0.66	—	0.27*	0.16
2. Employee engagement	3.43	0.79	0.27*	—	0.36**
3. Employee satisfaction	3.31	0.80	0.16	0.36**	—

Note. M = mean; SD = standard deviation. $p < .05$; $p < .001$. AI-HRM and satisfaction were measured on five-point scales, whereas engagement was measured on a scale ranging from 0 to 6.

AI-HRM had a positive correlation with employee engagement ($r = 0.27$, $p < .05$). Employee engagement was also positively correlated with employee satisfaction ($r = 0.36$, $p < .001$). Both correlations were statistically significant at the reported levels. In contrast, the correlation between AI-HRM and employee satisfaction was positive but not statistically significant ($r = 0.16$).

The mean scores were 3.23 for AI-HRM, 3.43 for engagement and 3.31 for satisfaction. These values describe the average responses within each construct. Because engagement used a different response scale from the other two variables, direct comparisons of the raw means should be avoided. Overall, the correlation results indicate that engagement was associated with both AI-HRM and employee satisfaction, whereas the bivariate relationship between AI-HRM and satisfaction was not statistically significant.

4.4 Hypothesis Testing

Regression-based mediation analysis was conducted to examine the proposed relationships among AI-HRM, employee engagement and employee satisfaction. Table 4 presents the estimated coefficients, standard errors, test statistics and significance levels for the direct paths and the indirect effect through engagement.

Table 4. Regression and Mediation Analysis Results

Hypothesis / Path	b	SE	t	p / 95% CI	Decision
H1: AI-HRM → Satisfaction (total effect, c)	0.195	0.115	1.69	.093	Not supported
H2: AI-HRM → Engagement (path a)	0.331	0.111	2.98	.004	Supported
H3: Engagement → Satisfaction (path b)	0.342	0.094	3.63	< .001	Supported
Direct effect: AI-HRM → Satisfaction (c′)	0.082	0.114	0.72	.472	Not significant
H4: Indirect effect (a × b)	0.113	—	—	[0.032, 0.220]	Supported

Note. b = estimated regression coefficient; SE = standard error; CI = confidence interval. The indirect effect was evaluated using a 95% bootstrap confidence interval based on 5,000 resamples.

The total effect of AI-HRM on employee satisfaction was positive but did not reach statistical significance ($b = 0.195$, $SE = 0.115$, $t = 1.69$, $p = .093$). Accordingly, H1 was not supported. The model for this relationship explained 2.5% of the variance in satisfaction ($R^2 = 0.025$).

AI-HRM was positively associated with employee engagement ($b = 0.331$, $p = .004$), supporting H2. The corresponding regression model explained 7.5% of the variance in engagement ($R^2 = 0.075$). Employee engagement was also positively associated with satisfaction after controlling for AI-HRM ($b = 0.342$, $p < .001$), supporting H3.

The estimated indirect effect of AI-HRM on satisfaction through engagement was 0.113. Its 95% bootstrap confidence interval ranged from 0.032 to 0.220 and did not include zero, providing statistical support for H4. In contrast, the direct effect of AI-HRM on satisfaction, after accounting for engagement, was not statistically significant (b = 0.082, p = .472). The full model explained 13.1% of the variance in employee satisfaction.

The results indicate an indirect-only mediation pattern in the analysed data: the indirect effect through engagement was statistically significant, whereas the total and direct effects were not. A statistically significant total effect is not a prerequisite for establishing an indirect effect under contemporary mediation analysis approaches (Hayes, 2018; Preacher & Hayes, 2008; Zhao et al., 2010). Nevertheless, the findings should be interpreted in accordance with the research design and the quality of the underlying data. Statistical mediation in cross-sectional survey data does not, by itself, establish a causal mechanism.

5. Discussion

The findings indicate that employee engagement may help explain the relationship between AI-driven human resource management (AI-HRM) and employee satisfaction. Although the total relationship between AI-HRM and satisfaction was not statistically significant, the indirect effect through engagement was significant. This pattern suggests that examining employee engagement alongside AI-enabled HR practices may provide a more informative understanding of how these practices relate to employee satisfaction.

The positive association between AI-HRM and employee engagement is consistent with the Job Demands–Resources (JD-R) model, which emphasises the role of job resources in promoting engagement (Bakker & Demerouti, 2007). AI-enabled HR practices that employees perceive as accessible, transparent and supportive may help facilitate work-related activities and professional development. However, the extent to which these practices contribute to engagement may depend on employees' experiences with the technologies and their perceptions of how the systems are implemented.

The positive relationship between engagement and satisfaction is also consistent with the view that employees' involvement in their work is related to their evaluations of their jobs. Social Exchange Theory provides a possible explanation: employees who perceive organisational practices as supportive may respond with greater involvement in their work (Blau, 1964). Affective Events Theory further suggests that workplace experiences can shape employees' job-related attitudes (Weiss & Cropanzano, 1996). Together, these perspectives provide a theoretical basis for examining engagement as a potential link between AI-HRM and employee satisfaction.

The absence of a statistically significant total effect, alongside a significant indirect effect, highlights the importance of distinguishing direct relationships from indirect pathways in mediation analysis. The results do not establish that AI-HRM improves satisfaction only through engagement, nor do they demonstrate a causal mechanism. Rather, they indicate that the proposed indirect relationship warrants further examination using appropriate empirical data and research designs.

The findings should also be considered in the context of how employees perceive AI-enabled HR practices. Factors such as perceived fairness, transparency, trust in AI and concerns about workplace monitoring may influence employee responses. Future research could examine whether these factors help explain differences in the relationships among AI-HRM, engagement and satisfaction.

6. Implications

6.1 Theoretical Implications

The study brings together the Job Demands–Resources model, Social Exchange Theory and Affective Events Theory to examine the proposed relationship between AI-HRM and employee satisfaction. By considering employee engagement as a mediator, the analytical framework distinguishes the overall relationship between AI-HRM and satisfaction from the indirect relationship operating through engagement. This provides a basis for further empirical investigation of how technology-enabled HR practices relate to employee attitudes.

The framework also highlights the importance of examining employee-related outcomes alongside the organisational efficiency benefits commonly associated with AI adoption. Further research using validated measurement instruments and appropriately collected employee data is needed to assess the explanatory value of the proposed relationships.

6.2 Practical Implications

For HR managers, the proposed framework highlights several areas that warrant attention when introducing AI-enabled HR systems. Organisations should communicate clearly about how AI is used in recruitment, performance

evaluation, employee development and other HR activities. Employees should understand the purpose of these systems, the information being processed and the role of human judgement in consequential decisions.

Organisations should also maintain appropriate human oversight, provide channels for employees to raise concerns and review AI-enabled decisions for fairness and consistency. Monitoring employee engagement and satisfaction may help HR teams understand how staff experience these technologies over time. These recommendations represent practical considerations for implementation; their effectiveness should be evaluated through empirical research rather than assumed from the present statistical relationships.

6.3 Implications for Researchers

The proposed model provides a framework for examining the relationships among AI-HRM, employee engagement and employee satisfaction. Future studies should use clearly documented sampling procedures, validated measurement instruments and transparent reporting of statistical analyses. Researchers may also examine whether trust in AI, perceived fairness and digital literacy influence the proposed relationships. Replication across industries and organisational settings would help establish whether the findings are consistent across different employee populations.

7. limitations and future research

Several limitations should be considered when interpreting the findings. First, the provenance of the dataset must be established before substantive conclusions can be drawn. If the analysis is based on simulated observations, the results demonstrate the analytical procedure rather than relationships among actual employees. If the dataset consists of genuine survey responses, the original questionnaires and respondent-level records should be used to verify the reported statistics.

Second, the cross-sectional design limits the ability to establish temporal ordering or causal relationships among AI-HRM, engagement and satisfaction. Longitudinal research could examine how employee perceptions change as organisations introduce or modify AI-enabled HR practices. Where feasible, future studies could also use designs that allow stronger assessment of causal relationships.

Third, the reported average variance extracted values were below the conventional 0.50 benchmark for all three constructs. This indicates that the measurement properties require further examination. The AI-HRM measure was developed for the study, and its reliability and validity should be evaluated in additional samples. The engagement and satisfaction instruments should also be checked against their cited sources to confirm item wording, scoring and appropriate use.

Fourth, the constructs were measured using different response scales. Although this does not automatically invalidate the analysis, researchers should ensure that scoring procedures are appropriate and clearly reported. The sample size of 112 respondents may also limit the precision and generalisability of the findings, particularly if the sample was not selected to represent a defined population.

Future research should therefore prioritise the verification and collection of genuine employee survey data, document the sampling and recruitment procedures, and validate the measurement instruments. Larger and more diverse samples could help assess the stability of the proposed relationships across industries and professional groups. Researchers could also investigate potential moderators, including trust in AI, perceived fairness, transparency and digital literacy. Finally, longitudinal or other appropriate research designs could provide stronger evidence about the direction and development of the relationships among AI-HRM, employee engagement and employee satisfaction.

8. Conclusion

This study examined the relationship between AI-driven human resource management (AI-HRM) and employee satisfaction, with employee engagement considered as a potential mediating factor. The results indicated that the total relationship between AI-HRM and employee satisfaction was not statistically significant. However, AI-HRM was positively associated with employee engagement, and engagement was positively associated with satisfaction. The indirect effect through engagement was statistically significant, whereas the direct effect was not. These findings highlight the importance of examining employee engagement when investigating the relationship between AI-enabled HR practices and employee satisfaction. Nevertheless, the results should be interpreted in light of the research design and measurement limitations. Further studies using verified employee survey data, validated measurement instruments and appropriate research designs are needed to assess the robustness and generalisability of the proposed relationships.

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