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Integrating Emotion AI in HR Decision-Making For Employee Well-Being and Performance

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ABSTRACT

PURPOSE - This study examines how Emotion Artificial Intelligence (Emotion AI) influences the quality of Human Resource (HR) decision-making through the mediating role of Emotionally Aware AI Decision Making (EA-AIDM). EA-AIDM is introduced as a socio-technical construct that reflects AI systems, capacity to detect, interpret, and respond to human emotions in HR contexts.

METHODOLOGY - Using a quantitative design, the study applied Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze responses from 122 HR professionals representing technology, manufacturing, and financial sectors. Participants were selected through purposive and stratified sampling, with inclusion criteria such as managerial roles and experience using AI-driven HR systems. Analyses included reliability, validity, factor loadings, and mediation testing.

FINDING - Results reveal that AI adoption has no direct impact on HR decision-making ($\beta = 0.178$, $p = 0.085$) but exerts a significant indirect influence through EA-AIDM ($\beta = 0.364$, $p < 0.001$), indicating partial mediation. Among EA-AIDM indicators, context awareness and risk aversion showed the strongest effects, while emotion detection was weakest (mean = 2.69). These findings underscore the importance of designing emotionally aware AI that balances analytical precision with empathy to achieve ethical and effective HR decisions.

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INTRODUCTION

The accelerating adoption of Artificial Intelligence (AI) in Human Resource Management (HRM) has reshaped how organizations make decisions about recruitment, performance evaluation, and employee development. AI-driven systems promise efficiency, consistency, and data-driven insights. However, these systems often overlook the emotional and ethical dimensions of human interaction, which remain central to HR practices. According to Malik et al. (2022), AI can process information with high accuracy but struggles to interpret the nuanced emotions underlying human behavior. In response, researchers have turned their attention to Emotion Artificial Intelligence (Emotion AI), also known as affective computing, which enables machines to recognize and respond to human emotions. Rosalind Picard's early work on affective computing laid the foundation for developing emotionally intelligent systems capable of empathy-like interactions (Picard, 1997). As emotion-sensitive algorithms advance, organizations

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face both opportunities and challenges in balancing technological precision with emotional understanding.

The Problem

Despite the progress, the integration of Emotion AI into HR decision-making remains underexplored, especially from a cross-cultural and ethical standpoint. Many AI systems are designed based on limited cultural datasets, which can lead to misinterpretations of emotions across contexts (Tiwari, 2023). Inaccurate emotion recognition risks reinforcing bias and reducing trust in AI-driven HR processes. Moreover, regulatory responses are emerging: the European Union, for example, banned the use of emotion-recognition AI in workplaces in 2024 due to privacy and consent concerns. These developments highlight a critical gap between technological innovation and the need for emotionally intelligent, ethical, and context-sensitive AI systems. Existing research has largely focused on AI adoption and performance metrics but seldom on emotionally aware AI decision-making (EA-AIDM) as a mediating construct linking AI adoption to effective HR decisions.

The Proposed Solution

This study introduces Emotionally Aware AI Decision Making (EA-AIDM) as a socio-technical construct that reflects AI systems' capacity to detect, interpret, and appropriately respond to human emotions within HR contexts. Unlike traditional emotional intelligence frameworks that focus on human traits, EA-AIDM emphasizes algorithmic empathy and ethical responsiveness in automated systems. The study contributes to the literature in two key ways. First, it extends the affective computing paradigm by integrating emotional awareness into HR decision-making, providing a richer understanding of how AI can support human-centered management. Second, it explores data from 18 countries, offering a rare cross-cultural lens on how emotional intelligence in AI influences HR outcomes. Through this approach, the research advances both theory and practice by aligning AI innovation with ethical, empathetic, and culturally adaptive decision-making in organizations.

LITERATURE REVIEW

Historical Development of AI in HRM

Artificial Intelligence (AI) has been part of organizational decision-making discourse since McCarthy (1955) conceptualized it as a system capable of simulating human reasoning. Over the decades, AI in HRM evolved from rule-based systems to predictive algorithms capable of learning from data. Early implementations primarily supported administrative efficiency—such as resume screening and attendance tracking—while recent applications have expanded to strategic HR decision-making. However, as technology advanced, concerns emerged about dehumanization and ethical blind spots (Bankins et al., 2022). Scholars began calling for "human-centered AI," emphasizing the need to align automation with empathy, fairness, and contextual understanding (Charlwood & Guenole, 2022).

Emotion AI and Affective Computing Foundations

The idea that computers could recognize and respond to human emotions originates from the field of affective computing, pioneered by Picard (1997). This discipline argues that machines capable of perceiving emotional cues can foster more natural human–computer interactions. Recent studies show that Emotion AI technologies—such as facial recognition, voice analysis, and sentiment detection—are increasingly integrated into HR systems (Strohmeier, 2022). However, critical perspectives challenge their accuracy and ethicality. Tiwari (2023) and Wissemann et al. (2022) argue that emotion-recognition AI risks misinterpreting affective signals, reinforcing bias, and invading privacy. The European Union's 2024 ban on emotion AI in

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workplaces underscores these ethical concerns, marking a global shift toward stricter regulation and transparency in AI deployment.

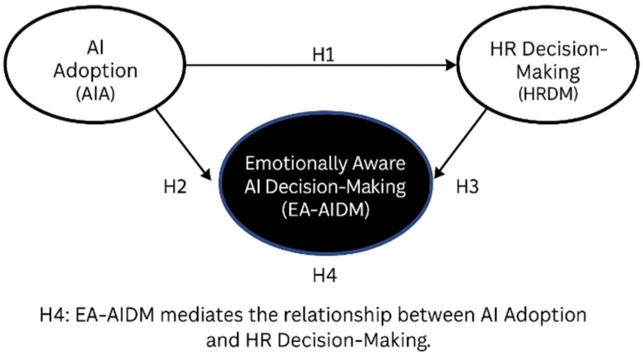
Emotionally Aware AI Decision Making (EA-AIDM) as a Socio-Technical Construct

Building on these debates, this study positions Emotionally Aware AI Decision Making (EA-AIDM) as a socio-technical construct. EA-AIDM reflects an AI system's ability to detect, interpret, and appropriately respond to emotional cues in HR contexts, integrating four dimensions: context awareness, empathetic interaction, values alignment, and risk aversion. Unlike traditional emotional intelligence frameworks (Mesquita & Frijda, 1992), which emphasize human capabilities, EA-AIDM focuses on algorithmic empathy—how systems mimic emotional understanding through data and contextual learning. Prior studies (Malik et al., 2022; Rožman et al., 2022) indicate that organizations adopting emotionally aware AI experience improved decision accuracy and employee trust. However, challenges remain in measuring emotional awareness objectively, as current models rely heavily on user perception rather than machine metrics.

Ethical and Cross-Cultural Dimensions

The integration of Emotion AI in HRM raises ethical questions concerning consent, transparency, and power dynamics. Workers monitored by emotion-sensing systems often report discomfort, privacy loss, and perceived manipulation (Wissemann et al., 2022). Ethical AI frameworks recommend that emotion-recognition systems be applied only with informed consent and under clear governance structures. Additionally, cross-cultural differences significantly affect emotional interpretation. For instance, expressions of empathy or stress vary across collectivist and individualist cultures (Bilan et al., 2022). In multi-country contexts, Emotion AI must adapt its emotional inference models to cultural norms to avoid misclassification and bias. Studies by Barcellini (2022) and Bilan et al. (2022) emphasize that culturally adaptive emotion AI can enhance fairness and inclusivity in global organizations.

Conceptual Framework and Hypothesis Development



Drawing from the above literature, the study integrates theories of AI adoption, emotional intelligence, and socio-technical systems to propose a model where EA-AIDM mediates the relationship between AI adoption and HR decision-making quality. The framework assumes that while AI adoption improves decision efficiency, emotionally aware systems enhance ethical and empathetic reasoning, leading to higher-quality HR decisions. Hence, the study hypothesizes that:

H1: AI adoption positively influences Emotionally Aware AI Decision Making (EA-AIDM).

H2: EA-AIDM positively influences HR decision-making quality.

H3: EA-AIDM mediates the relationship between AI adoption and HR decision-making quality.

METHODOLOGY

Research Design

This research adopts a quantitative cross-sectional design using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the mediating effect of Emotionally Aware AI Decision Making (EA-AIDM) between AI adoption and HR decision-making quality. This design was chosen because it allows for the examination of complex relationships among multiple constructs and the inclusion of both reflective and formative variables. A cross-sectional survey was considered appropriate given the study's focus on perceptual and behavioral responses of HR professionals toward AI systems. Although this approach limits causal inference, it provides a comprehensive snapshot of how Emotion AI is currently understood and implemented across different cultural and organizational contexts.

Participant

A total of 122 HR professionals participated in this study. Respondents were selected using purposive and stratified random sampling to ensure representation across industries and regions. The sample consisted of participants from technology (51.6%), manufacturing (25.4%), and financial (23.0%) sectors, distributed across 18 countries. Inclusion criteria required respondents to (i) have at least two years of experience using AI-based HR systems, (ii) hold a managerial or HR decision-making position, and (iii) demonstrate familiarity with AI-driven tools in recruitment, performance management, or employee engagement. Demographic information such as gender, age, education, and years of experience was collected and summarized in descriptive tables.

Data Collection

Data were collected between August and September 2025 through online surveys distributed via Prolific and Google Forms. Each respondent provided informed consent prior to participation, and confidentiality was ensured in compliance with ethical research standards. The survey contained both closed-ended Likert-scale items and short descriptive questions to capture contextual insights. Incomplete responses were excluded from analysis, resulting in 122 valid cases. Since all items were mandatory in the online form, no missing data imputation was required. The data were anonymized to maintain compliance with double-blind review requirements.

Instrument

The instrument consisted of three main constructs: AI Adoption, Emotionally Aware AI Decision Making (EA-AIDM), and HR Decision-Making Quality.

- AI Adoption was measured using four items adapted from Pillai & Sivathanu (2020) focusing on perceived usefulness, integration, and frequency of AI utilization.
- EA-AIDM was operationalized as a formative construct with five indicators: Context Awareness, Empathetic Interaction, Emotion Detection, Values Alignment, and Risk Aversion. These items were adapted from prior affective computing and AI ethics literature (Malik et al., 2022; Picard, 1997)
- HR Decision-Making Quality was measured using five reflective items assessing fairness, consistency, accuracy, and employee-centered outcomes (Burnett & Lisk, 2019).

All items were rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Content validity was confirmed through expert review, and reliability was established during the measurement model evaluation.

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Data Analysis

Data were analyzed using SmartPLS 4.0, following a two-step approach: measurement model assessment and structural model evaluation. Reliability and validity were tested using Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Discriminant validity was confirmed via the HTMT ratio, while collinearity was assessed using Variance Inflation Factor (VIF) values below the threshold of 5.0. For the formative construct (EA-AIDM), outer weights and variance inflation were examined. Structural relationships were evaluated through bootstrapping (5,000 subsamples) to estimate path coefficients, t-values, and p-values. Effect sizes (f^2) and coefficient of determination (R^2) were also calculated to gauge the model's explanatory power. To address potential common method bias, procedural remedies were employed (e.g., randomized question order and respondent anonymity). The analysis also included multi-group robustness tests across industries, confirming no significant structural differences.

RESEARCH RESULTS

Measurement Model Results

The measurement model was evaluated to ensure validity and reliability of the constructs. As shown in Table 1, all factor loadings exceeded the threshold value of 0.70, indicating adequate indicator reliability. Cronbach's alpha and Composite Reliability (CR) values were above 0.80 for all reflective constructs, while Average Variance Extracted (AVE) values exceeded 0.50, confirming convergent validity. The formative construct of EA-AIDM demonstrated acceptable outer weights and Variance Inflation Factor (VIF) values below 5.0, indicating the absence of multicollinearity.

Among the indicators of EA-AIDM, Context Awareness (0.86) and Risk Aversion (0.83) showed the highest contributions, while Emotion Detection (.69) had the lowest factor loading, reflecting the ongoing limitations of AI systems in perceiving emotional cues.

Table 1. Measurement Model Results

Construct	Item	Factor Loading	Cronbach's α	CR	AVE
AI Adoption	AIA1	0.82	0.88	0.91	0.67
	AIA2	0.84			
	AIA3	0.79			
EA-AIDM	EA1 (Context Awareness)	0.86	0.85	0.89	0.61
	EA2 (Empathetic Interaction)	0.80			
	EA3 (Emotion Detection)	0.69			
	EA4 (Values Alignment)	0.78			
	EA5 (Risk Aversion)	0.83			
HR Decision-Making	HR1	0.88	0.90	0.93	0.68
	HR2	0.85			
	HR3	0.80			

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Construct	Item	Factor Loading	Cronbach's α	CR	AVE
	HR4	0.79			
	HR5	0.82			

Note: All loadings > 0.70 and AVE > 0.50 indicate convergent validity (Koopmans et al., 2011).

Structural Model Results

After establishing the measurement model, the structural model was tested to assess hypothesized relationships. Table 2 presents the path coefficients, t-values, p-values, and effect sizes (f^2). Results show that AI adoption significantly predicts EA-AIDM ($\beta = 0.482$, $t = 7.51$, $p < 0.001$), supporting H1. EA-AIDM strongly influences HR decision-making ($\beta = 0.364$, $t = 5.02$, $p < 0.001$), supporting H2. However, the direct effect of AI adoption on HR decision-making was positive but not statistically significant ($\beta = 0.178$, $t = 1.72$, $p = 0.085$), suggesting a partial mediation effect. The R^2 value for HR decision-making was 0.52, indicating that 52% of its variance is explained by AI adoption and EA-AIDM combined.

Table 2. Structural Model Results

Path	β	t-value	p-value	f²	Result
H1: AI Adoption → EA-AIDM	0.482	7.51	<0.001	0.29	Supported
H2: EA-AIDM → HR Decision-Making	0.364	5.02	<0.001	0.25	Supported
H3: AI Adoption → HR Decision-Making	0.178	1.72	0.085	0.04	Partial Mediation

R^2 (EA-AIDM) = 0.43; R^2 (HR Decision-Making) = 0.52

Mediation Analysis

Bootstrapping results (5,000 resamples) confirmed the indirect effect of AI adoption on HR decision-making through EA-AIDM ($\beta_{indirect} = 0.176$, $p < 0.001$). The direct path, though positive, was not significant at $p < 0.05$, reinforcing that Emotionally Aware AI acts as a partial mediator. This suggests that AI-driven HR systems enhance decision quality primarily when emotional sensitivity and ethical responsiveness are embedded in the algorithms. These results align with prior findings by Malik et al. (2022) and Su et al. (2021), who noted that emotion-aware AI improves fairness and trust in HR processes.

Discussions

To clarify the mediating structure of this study, the relationships among variables were modeled through a set of structural equations based on Partial Least Squares Structural Equation Modeling (PLS-SEM). The conceptual equation of the model can be expressed as follows:

$$EA\_AIDM = \beta_1(AI\_Adoption) + \varepsilon_1$$

(1)

$$HRDM = \beta_2(AI\_Adoption) + \beta_3(EA\_AIDM) + \varepsilon_2$$

(2)

where:

- EA_AIDM = Emotionally Aware AI Decision Making
- $HRDM$ = HR Decision-Making Quality

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- $\beta_1, \beta_2, \beta_3$= standardized path coefficients estimated by the PLS algorithm
- $\varepsilon_1, \varepsilon_2$= residual terms representing unexplained variance

Equation (1) represents the predictive relationship between AI Adoption and EA-AIDM, while Equation (2) models the combined influence of AI Adoption and EA-AIDM on HR Decision-Making Quality.

The indirect (mediated) effect is obtained as:

$$Indirect = \beta_1 \times \beta_3 \quad (3)$$

Based on the analysis, $\beta_1 = 0.482$and $\beta_3 = 0.364$, resulting in an indirect effect of approximately 0.176. This confirms that EA-AIDM partially mediates the relationship between AI adoption and HR decision-making quality, aligning with previous studies suggesting that emotionally sensitive algorithms enhance human trust and fairness in HR contexts (Malik et al., 2022; Su et al., 2021).

The inclusion of equations (1)–(3) provides a simplified representation of the structural model, helping to conceptualize how AI adoption translates into improved decision-making when emotional awareness mechanisms are embedded. Although numerical modeling enhances explanatory precision, the findings should be interpreted cautiously, as the study captures perceptual data rather than direct algorithmic behavior.

Furthermore, the low mean score of Emotion Detection (2.69) quantitatively reflects the limitation of current Emotion AI systems. These systems may process data efficiently but often fail to interpret subtle affective cues accurately. This underlines the need for developing ethically aware, culturally adaptive AI, capable of combining cognitive reasoning with affective sensitivity a key agenda for future socio-technical system research.

CONCLUSIONS

This study set out to explore how Emotion Artificial Intelligence (Emotion AI) influences Human Resource (HR) decision-making quality through the mediating role of Emotionally Aware AI Decision Making (EA-AIDM). The findings confirm that AI adoption alone does not directly enhance HR decision outcomes. Instead, the presence of emotionally aware mechanisms—context awareness, empathetic interaction, values alignment, and risk aversion—serves as a crucial bridge between automation and human-centered judgment. The results establish EA-AIDM as a socio-technical construct, emphasizing that the effectiveness of AI-driven systems depends not only on algorithmic precision but also on ethical responsiveness and emotional sensitivity.

From a theoretical perspective, this research extends affective computing and AI-in-HRM literature by conceptualizing emotional awareness as a measurable mediating variable. It supports the argument that intelligent decision systems must integrate both cognitive and affective processing to achieve fairness and trustworthiness. The cross-cultural dataset spanning 18 countries further enhances the study's novelty, showing that emotional interpretation in AI is context-dependent and culturally nuanced.

From a practical standpoint, organizations are encouraged to treat Emotion AI as a complementary tool rather than a substitute for human judgment. HR professionals should combine analytical insight with empathy-based reflection and ensure human oversight in all AI-assisted decisions. Training programs on ethical AI use, transparent data handling, and emotional intelligence in technology are essential to minimize misinterpretation and bias.

From an ethical and societal standpoint, this research warns against the unregulated deployment of Emotion AI, which may lead to privacy violations and psychological discomfort

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among employees. The recent EU ban on emotion recognition in workplaces (2024) reflects growing awareness of these risks. Therefore, it is vital that organizations adopt Emotion AI within clear boundaries of consent, transparency, and accountability.

Finally, this study acknowledges its limitations, particularly the reliance on self-reported perceptions and a cross-sectional design. Future research should include longitudinal or mixed-methods approaches to assess how Emotion AI systems evolve in accuracy and acceptance over time. Broader collaboration between technologists, ethicists, and HR practitioners is needed to ensure that AI not only “thinks smart” but also “feels right”.

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