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AI ADOPTION AND HRM EFFECTIVENESS IN LEBANON: THE MEDIATING ROLE OF DECISION-MAKING AND THE MODERATING ROLE OF ETHICAL GOVERNANCE

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Abstract
This study investigates the impact of artificial intelligence (AI) adoption on human resource management (HRM) effectiveness within Lebanese organisations, a context marked by institutional fragility and cultural complexity. Drawing upon socio-technical systems theory, the technology acceptance model, the technology–organisation–environment framework, and ethical governance theory, a conceptual model was developed to test direct and indirect effects of AI adoption. Survey data from 349 HR professionals were analysed using structural equation modelling. Results show that AI adoption significantly enhances both decision-making quality and HRM effectiveness. Decision-making quality partially mediates the AI–effectiveness relationship, while ethical AI governance strengthens both direct and indirect effects. The findings underscore that responsible AI integration can deliver strategic HR benefits even in fragile economies when supported by sound governance and informed human oversight. The study contributes to HRM scholarship by extending technology adoption models to unstable economic contexts and offering practical insights for developing ethical and effective AI-enabled HR systems.
Keywords: Artificial Intelligence, Human Resource Management, Decision-Making, Ethical Governance, Fragile Economies, Lebanon

1. Introduction

The rise of AI and its implications for HRM

The early twenty-first century heralded the emergence of artificial intelligence as a powerful set of technologies that augment or automate human cognition. Once confined to research laboratories, AI capabilities—particularly machine learning (ML), natural language processing (NLP), robotic process automation (RPA) and generative models—are now embedded in everyday organizational systems. These technologies enable computers to recognize patterns, learn from data, interpret human language, generate content and carry out complex tasks previously reserved for humans. Within the domain of human resource management, AI applications extend beyond simple automation of administrative tasks. They facilitate predictive talent analytics, algorithmic candidate screening, automated performance evaluations, personalized learning recommendations, sentiment analysis of employee feedback, chatbots for HR enquiries and workforce planning based on real-time data. Such innovations promise to increase efficiency, reduce costs and enhance strategic decision-making in HRM (Tambe, Cappelli & Yakubovich, 2019). AI also raises fundamental questions about the role of humans in HR functions that traditionally relied on social judgment, empathy and tacit knowledge (Chansoriya & Shukla, 2019).

Opportunities and challenges in fragile economies

Although most empirical studies of AI-enabled HRM have been conducted in developed economies with strong institutions and digital infrastructure, there is increasing interest in how AI adoption unfolds in fragile contexts. Fragile economies face resource scarcity, regulatory ambiguity, unstable institutions and cultural practices that may resist digital change. In the Middle East and North Africa (MENA) region, AI adoption in HRM remains patchy. Lebanon presents a particularly compelling case: a country in chronic financial crisis, lacking efficient governance and digital readiness but with a highly educated population and diaspora links. Lebanese organizations must navigate electricity outages, currency fluctuations, political instability and cultural norms such as wasta—the use of personal networks and influence. These conditions raise questions about how AI can be integrated into HR processes and whether it can improve decision quality and organizational effectiveness in the absence of robust formal institutions. There is also the ethical challenge of deploying AI in HR practices—ensuring privacy, fairness and transparency while dealing with data scarcity and biases (Kasouha, Tannous & Nasrallah, 2024). Without careful governance, AI could reproduce or even exacerbate existing inequalities (Raghavan et al., 2020).

Research problem, questions and objectives

Existing literature has focused heavily on the technical performance of AI or on business cases from large corporations. Little is known about how AI affects HRM effectiveness in fragile economies and the mechanisms through which these effects operate. Does AI adoption directly improve HRM outcomes, or is its impact mediated by improvements in the quality of HR decision-making? Under what conditions are these relationships strengthened or weakened? To address these gaps, this study investigates AI adoption and HRM effectiveness in Lebanon through the following research question:

How does the adoption of Artificial Intelligence influence HRM effectiveness, and what roles do decision-making quality and ethical governance play in shaping this relationship within Lebanese organizations?

To operationalize this question, five specific objectives guide the research:

Assess the extent of AI adoption in Lebanese HR functions and its direct impact on HRM effectiveness.

Investigate how AI adoption influences the quality of HR decision-making and whether decision quality mediates the AI–effectiveness relationship.

Examine the moderating role of ethical AI governance on the effects of AI adoption and decision quality.

Identify HR practitioners' perceptions, readiness and concerns regarding AI adoption and governance in Lebanon.

Contextualize findings within the economic, cultural and institutional realities of Lebanon to derive practical and policy implications.

Significance of the study

This research contributes to the HRM literature by integrating decision-making quality and ethical AI governance into a unified model of AI adoption in HRM. It extends classical adoption models—such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990)—into a fragile context where institutional instability and cultural norms influence technology outcomes. It also explores how socio-technical systems theory (Trist & Bamforth, 1951; Thomas, 2024) and decision-making theory (Simon, 1997) intersect with ethical governance frameworks (Jobin, Ienca & Vayena, 2019; Floridi & Cowls, 2022) to shape AI's impact on HRM. By focusing on Lebanon, the study offers insights for policymakers and practitioners in similar economies that seek to harness AI responsibly. It emphasizes the need for transparent governance structures, bias auditing and employee engagement to ensure that AI in HRM enhances fairness and trust rather than diminishing them.

2. Literature Review

Theoretical foundations

Socio-Technical Systems (STS) Theory: STS theory posits that organizational performance emerges from the alignment of social systems (people, culture, relationships) and technical systems (tools, workflows, technology) (Trist & Bamforth, 1951). AI adoption in HRM reshapes this balance by introducing algorithmic agents into people processes. Integrating AI successfully requires attention to human capabilities, organizational culture and governance structures (Thomas, 2024; Yu, Huang & Wang, 2023). A mismatch between advanced analytics and social norms can undermine performance.

Decision-Making Theory: According to decision-making theory, rationality is bounded by limited information and cognitive constraints (Simon, 1997). Evidence-based management advocates rely on data to improve decisions but also recognize the importance of judgement and context (Barends & Rousseau, 2018). AI tools can expand decision-makers' information processing capacity but may also introduce new biases if training data are skewed (Gupta, 2024). Empirical evidence suggests that hybrid human–AI decision systems deliver the best outcomes when machines handle data-heavy tasks and humans provide ethical reasoning (Malin, Schmidt & Krause, 2024).

Ethical Governance Theory: Ethical governance frameworks emphasize accountability, transparency, fairness and human oversight in AI systems (Jobin, Ienca & Vayena, 2019; Floridi & Cowls, 2022). In HRM, ethical AI governance requires clear policies on data use, algorithmic audit trails, explainability and employee participation (Aldossari & Payne, 2023; Rodgers, Gupta & Kumar, 2023). Without such mechanisms, AI can reinforce discrimination, violate privacy and erode trust (Ajunwa, 2020; Raghavan et al., 2020). Ethical governance thus moderates the positive effects of AI on HR outcomes by ensuring legitimacy and social license.

Technology Adoption Models: The Technology Acceptance Model (TAM) explains adoption through perceived usefulness and ease of use (Davis, 1989), while the TOE framework considers organizational and environmental factors (Tornatzky & Fleischer, 1990). Extensions of these models incorporate culture, leadership and digital readiness (Islam & Aldaihani, 2023; Khan, Ali & Hussain, 2024). In fragile economies, readiness is hindered by infrastructure deficits, unstable regulations and cultural practices like waste (Nassar, Messarra & Assaf, 2022). AI adoption is more likely when leaders champion innovation, resources permit experimentation and external pressures (e.g., donor requirements) encourage digital transformation (Choueiri & El Hajj, 2025).

AI adoption and HRM effectiveness

AI adoption is widely touted as transforming HR from a transactional function to a strategic partner. Global evidence shows that AI-driven HR processes enhance efficiency, improve candidate matching, personalize training and generate predictive workforce insights (Bondarouk, Meijerink & Lepak, 2022; Meijerink, Bondarouk & Lepak, 2021). However, adoption is uneven. In developed economies, AI integration benefits from reliable data, advanced infrastructure and strong regulatory safeguards. In the MENA region, adoption has lagged due to resource shortages and cultural reluctance (AlDmour et al., 2022). In Lebanon, evidence suggests that some private firms and donor-funded projects have begun using AI for recruitment and performance management, but these initiatives are sporadic and face pushback due to lack of trust and digital literacy (Saleh, Obeid & Khalil, 2025; Choueiri & El Hajj, 2025). Research on HRM effectiveness in fragile settings emphasizes resilience, fairness and sustainability rather than purely efficiency (Becker & Huselid, 1998; Ulrich et al., 2012). AI's impact on these broader outcomes remains underexplored.

Decision-making quality in AI-enabled HRM

Decision quality refers to the accuracy, fairness, transparency and speed of decisions. AI promises to improve decision quality by processing vast amounts of structured and unstructured data, detecting hidden patterns and generating real-time insights (Jarrahi, 2018; Tambe, Cappelli & Yakubovich, 2019). Studies report that AI tools increase consistency and reduce personal bias in recruitment, performance evaluation and talent management (Strohmeier, 2020; Malin, Schmidt & Krause, 2024). Yet critics warn that algorithms can reproduce historic biases if trained on skewed data and that opaque "black box" models may reduce transparency (Binns et al., 2022; Sachan, Sharma & Dubey, 2024). High-quality decision-making therefore depends on balancing automated analytics with human judgement and ensuring algorithmic fairness audits and explainability (Gupta, 2024). In fragile contexts, low digital literacy and weak oversight magnify risks of misuse.

Ethical AI governance and transparency

Growing concern over algorithmic discrimination, privacy violations and surveillance has made ethical AI governance a central issue. Responsible AI frameworks propose principles—such as fairness, accountability, transparency and data protection—but translating these into HR practice is challenging (Jobin, Ienca & Vayena, 2019; Floridi & Cowls, 2022). In HRM, ethical governance involves documenting data sources, regularly auditing algorithms for bias, involving diverse stakeholders in system design and giving employees avenues to contest decisions (Rodgers, Gupta & Kumar, 2023; Purohit & Banerjee, 2025). Lebanon lacks comprehensive AI regulation. Law 81/2018 on Electronic Transactions covers data protection but has loopholes, leaving employers and employees without clear safeguards (Zarif, 2022). Scholars argue for context-specific ethics frameworks that respect local culture and resource constraints (Daoud, 2023; Fadlallah, 2025). Organizations must therefore proactively implement internal governance and transparency measures to build trust.

HRM effectiveness in the digital age

Traditional measures of HRM effectiveness focus on administrative efficiency, cost reduction and alignment with organizational strategy (Becker & Huselid, 1998; Ulrich et al., 2012). In a digital era, effectiveness also encompasses employee engagement, adaptability, data-driven insights and fairness (Meijerink, Bondarouk & Lepak, 2021). AI-enabled HRM can potentially improve recruitment speed, automate routine tasks, personalize learning and provide predictive analytics for workforce planning (Marler & Boudreau, 2017; Bondarouk, Meijerink & Lepak, 2022). However, effectiveness in fragile settings extends to resilience, equity and social license. HR systems must support employees through economic crises, maintain fairness in recruitment and performance, and protect organizational legitimacy amidst socio-political instability (Harb & Atallah, 2025; ESCWA, 2024). This study measures HRM effectiveness as a multidimensional construct reflecting operational efficiency, strategic alignment, fairness and employee perceptions.

3. Research Model and Hypotheses

H1: AI adoption in HRM positively influences decision-making quality.

H2: AI adoption in HRM positively influences HRM effectiveness.

H3: Decision-making quality positively affects HRM effectiveness.

H4: Decision-making quality mediates the relationship between AI adoption and HRM effectiveness.

H5: Ethical AI governance moderates the relationship between decision-making quality and HRM effectiveness, such that the relationship is stronger under conditions of high ethical AI governance.

H6: Ethical AI governance moderates the direct relationship between AI adoption in HRM and HRM effectiveness, strengthening the effect when ethical governance is high.

4. Methodology

Research design and sample

The study adopts a cross-sectional survey design, collecting data from HR professionals working in Lebanon. Purposive sampling was used to reach participants with knowledge of AI-enabled HRM. Survey links were disseminated through HR associations, professional networks, universities and social media. A total of 349 valid responses were received, exceeding the recommended minimum for structural equation modelling (Kline, 2016). Respondents represented diverse demographics and organizational contexts: the majority were male (60.5 %); the dominant age group was 35–44 years (55.3 %); mid-level professionals with 4–6 years of experience made up 31.8 %; most worked in HR management or departmental leadership roles; and organizations ranged from small (< 50 employees) to large (> 500 employees). Sector representation included private companies (41.8 %), academic institutions (25.5 %), non-governmental organizations (17.2 %) and public bodies (10.3 %). The sample thus captured a broad cross-section of Lebanon's HR ecosystem.

Instrumentation

The survey instrument comprised five sections: (i) demographic information; (ii) AI adoption in HRM; (iii) decision-making quality; (iv) ethical AI governance; and (v) HRM effectiveness. Items were measured on five-point Likert scales (1 = strongly disagree, 5 = strongly agree). Constructs were adapted from established scales: AI adoption items from Marler & Boudreau (2017) and Strohmeier (2020); decision-making quality items from Simon (1979) and evidence-based management literature; ethical governance items from Jobin, Ienca & Vayena (2019) and Floridi & Cowls (2022); HRM effectiveness items from Becker & Huselid (1998) and Ulrich et al. (2012). Survey items measured perceptions of AI usage in key HR functions (recruitment, onboarding, training), training adequacy, alignment with strategic goals, decision-making speed, transparency, consistency, ethical oversight, fairness and HR outcomes. Cronbach's alpha values for all constructs exceeded 0.87, indicating strong internal consistency.

Data analysis

Data were analyzed using SPSS and AMOS. Descriptive statistics profiled the sample and summarized attitudes towards AI adoption, decision quality, governance and HRM effectiveness. Reliability and validity of constructs were tested via Cronbach's alpha, factor loadings, composite reliability (CR) and average variance extracted (AVE). All CR values exceeded 0.70 and AVE values exceeded 0.50, confirming convergent validity; discriminant validity was established by comparing the square root of AVE with inter-construct correlations. Regression analyses examined direct effects of AI adoption on decision quality and HRM effectiveness and the effect of decision quality on HRM effectiveness (H1–H3). Mediation analysis used Baron & Kenny's (1986) steps and bootstrapping to test H4. Moderation analysis assessed whether ethical governance strengthened the decision quality–effectiveness and AI adoption–effectiveness relationships (H5–H6) using interaction terms. Structural equation modelling evaluated the overall model fit using indices such as CMIN/df, RMSEA, CFI, TLI, GFI and AGFI. The hypothesized model achieved a good fit (CMIN/df = 2.105; RMSEA = 0.056; CFI = 0.942; TLI = 0.926; GFI = 0.911; AGFI = 0.888).

5. Results

Descriptive findings

AI adoption: AI tools were in use across recruitment, onboarding, training and decision-support functions in many organizations, though adoption varied. About 52.7 % of respondents agreed or strongly agreed that their organization had adopted AI for key HR tasks; 47.8 % felt AI was actively used in HR decision-making; and 50.4 % said adoption aligned with strategic HR goals. However, around 15 % strongly disagreed on all items, signaling pockets of non-implementation and resistance. Training adequacy and system upgrades lagged behind adoption levels, with 20–23 % of participants disagreeing that HR staff were sufficiently trained or systems upgraded.

Decision-making quality: A majority of participants reported that AI improved data quality (54.7 %), accelerated decision-making (54.5 %) and increased accuracy (57.3 %). Many agreed that AI enhanced consistency (51.6 %), transparency (51.3 %) and reduced subjectivity (55 %). Nonetheless, a notable minority (15–22 %) expressed disagreement and a further 12–24 % were neutral, indicating skepticism and uncertainty about AI-generated decisions.

Ethical AI governance: Perceptions of governance were mixed. While 54.2 % agreed that AI systems were monitored for fairness and bias and 50.5 % said HR professionals reviewed AI decisions, only 42.5 % felt their organization ensured transparency in AI processes and 45.9 % believed employee data were protected under clear privacy guidelines. High neutrality (18–29 %) and dissent (10–22 %) suggest gaps in communication, transparency and ethical oversight.
HRM effectiveness: More than half of respondents perceived improvements in HRM efficiency, strategic alignment, employee engagement and data-driven talent management following AI adoption (56–60 %). However, perceptions of fairness and consistency were more mixed: 23–33 % disagreed or were neutral about AI improving fairness and consistency, indicating that AI benefits may be unevenly distributed.
Reliability
Cronbach's alpha values demonstrated high reliability: AI adoption ($\alpha = 0.874$); decision quality ($\alpha = 0.939$); ethical governance ($\alpha = 0.896$); HRM effectiveness ($\alpha = 0.943$). This justified the use of summed scores for further analysis.
Hypothesis testing
H1: AI adoption positively influenced decision-making quality. Regression results showed a strong positive effect ($\beta = 0.836$, SE = 0.029, $p < 0.001$) with AI adoption explaining 71.2 % of variance in decision quality ($R^2 = 0.712$). The relationship was statistically significant ($t = 29.264$).
H2: AI adoption positively influenced HRM effectiveness. AI adoption had a significant direct effect on HRM effectiveness ($\beta = 0.838$, SE = 0.035, $p < 0.001$), explaining 62.3 % of variance ($R^2 = 0.623$). Despite a strong effect, the standardized coefficient ($\beta = 0.789$) was lower than the effect of decision quality on HRM effectiveness, suggesting mediation.
H3: Decision-making quality positively affected HRM effectiveness. Decision quality was a very strong predictor of HRM effectiveness ($\beta = 0.872$, SE = 0.033, $p < 0.001$), explaining 66.3 % of variance ($R^2 = 0.663$). The strong effect emphasizes the importance of high-quality decisions in achieving HRM effectiveness.
H4: Decision-making quality mediated the relationship between AI adoption and HRM effectiveness. Baron & Kenny's steps showed that AI adoption significantly predicted decision quality and HRM effectiveness; decision quality significantly predicted HRM effectiveness; and the direct effect of AI adoption on HRM effectiveness reduced when decision quality was included. A bootstrapped Sobel test confirmed partial mediation. This means AI adoption influences HRM effectiveness both directly and indirectly through better decision-making.
H5: Ethical AI governance moderated the effect of decision quality on HRM effectiveness. Interaction analysis showed that the interaction term (decision quality × ethical governance) significantly predicted HRM effectiveness ($\beta = 0.025$, SE = 0.001, $t = 29.628$, $p < 0.001$) with a high standardized coefficient ($\beta = 0.847$). Under high ethical governance, the positive effect of decision quality on HRM effectiveness was stronger.
H6: Ethical AI governance moderated the direct relationship between AI adoption and HRM effectiveness. The interaction term between AI adoption and ethical governance also had a significant positive effect on HRM effectiveness ($\beta = 0.027$, SE = 0.001, $t = 25.907$,

$p < 0.001$). When ethical governance was high, AI adoption had a stronger direct influence on HRM effectiveness.

6. Discussion

The study provides empirical evidence that AI adoption can enhance HRM effectiveness in fragile economies when it improves decision quality and is governed ethically. In Lebanon's volatile context, AI is not merely a productivity tool; it is a catalyst for more objective, transparent and meritocratic HR practices. The strong effect of AI on decision-making quality supports decision-making theory: AI extends human cognitive limits by processing data faster and more accurately, thereby reducing bounded rationality (Simon, 1997). This is critical in Lebanon where informal practices such as wasta often influence HR decisions, leading to perceptions of unfairness (Nassar, Messarra & Assaf, 2022). AI algorithms, if properly designed and audited, can challenge nepotism by making recommendations based on objective criteria. However, the study cautions that algorithmic advice must be paired with human oversight to ensure context sensitivity and empathy.

The mediation finding underscores that the primary pathway through which AI improves HRM effectiveness is via better decisions rather than automation per se. This aligns with the socio-technical view that effectiveness arises from integrating technological and social subsystems. For fragile economies, investment in AI must be accompanied by efforts to upgrade decision processes, train HR staff in data literacy and establish feedback loops for continuous improvement. Without these organizational changes, AI may simply automate inefficient processes or replicate biases embedded in historical data.

Ethical AI governance emerges as a crucial boundary condition. In Lebanon, weak regulatory frameworks mean organizations themselves must establish and enforce governance mechanisms. The significant moderation effects indicate that high governance standards—characterized by transparency, privacy protection, bias monitoring and stakeholder involvement—amplify the benefits of AI adoption and decision quality. Ethical governance increases trust among employees, reduces fears of surveillance and ensures that AI systems are aligned with organizational values and societal norms. Conversely, low governance undermines trust and can negate the positive impacts of AI. This finding parallels arguments in the global literature that governance is essential for trustworthy AI (Floridi & Cowls, 2022; Jobin, Ienca & Vayena, 2019) and highlights its importance in fragile contexts.

The results also contribute to debates on the role of AI in mitigating or perpetuating bias. Some scholars warn that AI inherits biases from data and may obscure discrimination behind technical complexity (O'Neil, 2016). Others argue that AI can promote fairness by removing human subjectivity if designed responsibly (Strohmeier, 2020). This study shows that in Lebanon, AI adoption—combined with ethical governance—can indeed reduce subjectivity and nepotism, suggesting that AI may disrupt rather than entrench discriminatory practices in contexts where nepotism is culturally embedded. This emphasizes the importance of algorithmic audits, diverse training data and participatory design.

Context matters. HRM effectiveness in fragile economies is not only about efficiency and cost; it involves resilience, equity and sustainability. AI's strategic value lies in enabling data-driven forecasting, personalized support for employees and proactive workforce planning. In a country grappling with economic shocks and brain drain, AI can help organizations retain talent by identifying flight risks and tailoring development programmed. However, these benefits will materialize only if organizations invest in digital infrastructure, address power and connectivity issues, and develop internal competencies to use AI responsibly.

7. Conclusion

Practical implications

For HR leaders in Lebanon and similar contexts, the findings suggest several actions. First, treat AI as an aid to decision-making rather than a replacement for human judgement. Invest in data quality, analytics skills and change management to ensure that AI tools enhance rather than undermine HR capabilities. Second, develop clear ethical governance frameworks: document data sources, perform regular bias audits, provide explain ability and involve employees in system design. Third, align AI adoption with organizational strategy and cultural values, and communicate openly with employees to build trust. Fourth, policymakers should develop context-appropriate regulations and support initiatives that build digital infrastructure and digital literacy. Finally, educational institutions and professional associations can play a role in training HR professionals on AI ethics, governance and data analysis.

Limitations and future research

Although this study provides important insights, it has limitations. Its cross-sectional design limits causal inference; longitudinal studies could examine how AI adoption and governance evolve over time. The self-reported measures may be subject to social desirability bias; future research could triangulate with objective performance data. The sample, though diverse, may overrepresent certain sectors or professionals with interest in AI; random sampling across industries could improve generalizability. The study focused on Lebanon; comparative research across multiple fragile economies would shed light on contextual differences. Future studies might also explore specific AI applications (e.g., chatbots, predictive analytics) and their distinct impacts on HR outcomes, as well as employee experiences and reactions to AI-driven HR systems.

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Supplementary Results and Detailed Commentary

Descriptive statistics: Demographic profile and organizational context

A closer look at the demographic data collected in the study provides insights into the composition of the HR workforce engaged in AI adoption. Gender distribution showed that 60.46 % of respondents identified as male, 35.82 % as female and 3.72 % preferred not to disclose their gender. This skew suggests that men still hold a majority of HR roles in Lebanon, though women represent more than one-third of the profession. Age distribution was heavily concentrated in the 35–44 year bracket (55.30 %), followed by 45–54 (17.19 %), 25–34 (14.33 %), under 25 (9.46 %) and over 55 (3.72 %). The dominance of mid-career professionals indicates that most respondents were seasoned enough to have strategic influence while still being digitally receptive. Years of experience mirrored this distribution: the largest group (31.81 %) had 4–6 years of HR experience, 27.22 % had more than 10 years, 15.47 % had 1–3 years and 14.61 % had less than one year. Only 10.89 % had 7–10 years of experience, suggesting a bimodal distribution of early-career and veteran professionals. This pattern may reflect retention challenges or career mobility in Lebanon's HR sector.

Professional positions further illuminate the strategic status of participants. The survey captured a high proportion of leadership roles: 28.4 % were department heads, 27.8 % HR managers and 20.9 % HR officers. Executives and directors comprised 9.2 %. The remaining categories—office managers, senior accountants, teachers, students, programmers and coordinators—each represented 1.7 % or less. Only 1.7 % of respondents were unemployed. This distribution confirms that the study tapped respondents with significant responsibility over HR processes, thereby enhancing the validity of their perspectives on AI adoption and governance. Sector representation showed that the largest share of participants worked in private organizations (41.8 %), followed by academic institutions (25.5 %), non-governmental organizations (17.2 %) and public sector bodies (10.3 %). A small number (1.7 % each) were students or independent consultants. The dominance of private and academic sectors underscores where AI experimentation in HRM may be concentrated, while the presence of public and NGO respondents suggests some diffusion beyond private enterprise.

The size of organizations also sheds light on the HR landscape. Firms with 50–199 employees constituted the majority (54.7 %), followed by small organizations with fewer than 50 employees (24.4 %), large organizations with 500+ employees (12.0 %) and mid-size firms with 200–499 employees (8.9 %). The prominence of mid-sized enterprises indicates that AI adoption is being considered by organizations that are large enough to require digital transformation but may lack the resources of multinationals. Many Lebanese firms fall within this range, reflecting the overall business distribution in the country. Collectively, the demographic data suggest that AI in HRM is being explored across diverse sectors, with mid-career, mid-level managers playing central roles.

Descriptive statistics: Attitudes towards AI adoption and governance

Beyond demographic variables, the survey gathered detailed responses on AI adoption, decision quality, ethical governance and perceived HRM effectiveness. AI adoption items revealed a spectrum of engagement. Over half of participants reported that AI tools were used for key HR functions such as recruitment, onboarding and training. However, training of HR staff was identified as a shortfall—around 36.7 % disagreed or were neutral about sufficient training provision. This gap underscores the importance of capacity building for successful AI adoption. Similarly, system upgrades lagged behind adoption, with over 37 % expressing disagreement or neutrality about the adequacy of technological infrastructure. These findings imply that while many Lebanese organizations are experimenting with AI, they may be doing so without fully integrated systems or trained personnel, which could limit effectiveness.

Respondents were fairly positive about AI-enabled decision-making. A majority agreed that AI improved data quality, sped up decision-making and enhanced accuracy. Perceptions of consistency, transparency and reduced subjectivity were also favorable, though a persistent minority remained skeptical. The neutral responses, ranging from 11.7 % to 24.1 %, suggest that many HR professionals are still uncertain about the reliability and fairness of AI recommendations. This hesitancy could stem from unfamiliarity with algorithmic processes or concerns about data bias. Organizations should address these concerns by providing training on how AI works and by emphasizing human oversight and ethical safeguards.

Views on ethical AI governance were more varied. While just over half of respondents acknowledged efforts to monitor AI systems for fairness and bias and to involve HR professionals in reviewing AI decisions, fewer were confident in transparency and privacy protections. A notable portion of participants either disagreed or neither agreed nor disagreed that employees were informed about AI usage and that a designated team or policy existed for AI ethics. These results reveal potential blind spots in organizational communication and governance structures. Employees may not fully understand how AI is used in HR decisions, leading to mistrust. Organizations should consider establishing dedicated AI ethics committees, publishing governance policies and fostering a culture of transparency.

Perceptions of HRM effectiveness suggested that AI was making inroads in efficiency, strategic alignment and employee engagement. More than half of participants saw improvements in these areas, and many believed that talent management had become more predictive and data-driven. However, fairness and consistency were more contentious. Nearly one-third of respondents either disagreed or felt neutral about AI leading to fairer or more consistent HR decisions. These findings underscore that AI adoption does not automatically translate into equitable outcomes; fairness must be designed and monitored intentionally through governance mechanisms.

Reliability and validity in depth

The robust reliability of the survey instrument supports the trustworthiness of the study's results. Cronbach's alpha coefficients exceeding 0.87 indicate that items within each construct consistently measured the underlying concept. Composite reliability (CR) values above 0.70 further support this. The average variance extracted (AVE) values, which were greater than 0.50 for all constructs, suggest that the items captured more variance of the construct than error variance, satisfying convergent validity. Discriminant validity was confirmed by ensuring that the square root of each construct's AVE was greater than its correlations with other constructs. This means that AI adoption, decision-making quality, ethical governance and HRM effectiveness are distinct yet related constructs. Such rigorous psychometric assessments strengthen the credibility of subsequent regression and SEM analyses.

Detailed regression results

The study employed multiple regression analyses to test direct effects. For H1, the model predicting decision-making quality from AI adoption revealed a strong coefficient of determination ($R^2 = 0.712$), indicating that over 71 % of the variance in decision quality can be explained by AI adoption. The unstandardized coefficient ($B = 0.836$) implies that each unit increase in AI adoption corresponds to a 0.836 unit increase in decision quality. The large t-value (29.264) and p-value (< 0.001) confirm that the effect is statistically significant. The standardized coefficient ($\beta = 0.844$) suggests a large effect size. These findings reinforce that AI usage in HR decisions is strongly associated with improvements in decision quality.

For H2, the regression of HRM effectiveness on AI adoption produced $R^2 = 0.623$, meaning that AI adoption explains approximately 62 % of the variance in HRM effectiveness. The unstandardized coefficient ($B = 0.838$) indicates that a one-unit increase in AI adoption yields a 0.838 unit increase in effectiveness, while the standardized coefficient ($\beta = 0.789$) signifies a large effect. The t-value of 23.962 and the p-value (< 0.001) confirm statistical significance. This demonstrates that organizations using AI are perceived as more effective in their HR functions, even before considering mediation or moderation effects.

H3 tested the effect of decision-making quality on HRM effectiveness. The resulting $R^2 = 0.663$ shows that decision quality explains 66 % of the variance in HRM effectiveness—slightly more than AI adoption alone. The unstandardized coefficient ($B = 0.872$) indicates a large effect of decision quality on HRM effectiveness. The t-value of 26.099 and the very small p-value highlight strong statistical significance. The standardized coefficient ($\beta = 0.814$) further underscores the large effect. Collectively, these results suggest that high-quality decision-making, whether supported by AI or not, is central to achieving effective HRM. AI matters, but its benefits are primarily realized through improved decision processes.

Mediation analysis explained

To test H4—the mediation effect of decision-making quality—the study followed Baron & Kenny's (1986) procedure. The first step established that AI adoption significantly predicts HRM effectiveness; the second showed that AI adoption predicts decision quality; the third demonstrated that decision quality predicts HRM effectiveness. Finally, when both AI adoption and decision quality were entered as predictors of HRM effectiveness, the coefficient for AI adoption decreased but remained significant. This reduction indicates partial mediation, meaning that decision quality transmits part of AI adoption's impact but not all of it. Bootstrapped confidence intervals for the indirect effect did not include zero, confirming significance. This partial mediation suggests that while AI adoption directly enhances HRM effectiveness to some extent, its main route is through enabling faster, fairer and more accurate decisions. Organizations should thus focus not just on deploying AI but on using AI to inform high-quality decision-making.

Moderation analysis: Interpreting interaction effects

Moderation analysis assessed how ethical AI governance influences the strength of the relationships between AI adoption, decision quality and HRM effectiveness. For H5, the interaction term between decision quality and ethical governance had a significant positive coefficient ($B = 0.025$, $\beta = 0.847$), indicating that when ethical governance is high, the positive association between decision quality and HRM effectiveness becomes stronger. Graphically, this means that organizations with robust governance derive greater benefits from high decision quality than those with weak governance. In organizations lacking ethical safeguards, improvements in decision quality may not translate fully into HRM effectiveness, possibly because employees or stakeholders mistrust the AI-assisted decisions.

For H6, the interaction between AI adoption and ethical governance also showed a significant positive effect on HRM effectiveness. The coefficient ($B = 0.027$, $\beta = 0.812$) suggests that ethical governance amplifies the direct effect of AI adoption. Organizations that adopt AI without adequate ethical frameworks may see limited improvements because employees are wary of AI decisions; in contrast, those with strong governance can capitalize on AI adoption to a greater extent. These moderation effects emphasize that AI's impact is not purely technological but also contingent on the organizational environment and governance mechanisms. Ethical governance acts as a catalyst, enhancing the positive outcomes of AI and decision quality.

Structural model assessment in detail

The structural equation model tested the full conceptual framework, integrating direct, indirect and moderated paths. Model fit indices provide a holistic evaluation: the Chi-square to degrees of freedom ratio (CMIN/df) was 2.105, below the conventional threshold of 3.00, indicating an acceptable level of model complexity relative to fit. The root mean square error of approximation (RMSEA) of 0.056 falls below the 0.08 threshold (and close to the more stringent 0.06), suggesting a good approximation of the population covariance matrix. The comparative fit index (CFI = 0.942) and Tucker-Lewis index (TLI = 0.926) exceed 0.90, indicating that the model explains the data substantially better than a null model. The goodness-of-fit index (GFI = 0.911) and adjusted GFI (AGFI = 0.888) further support the model's adequacy. The root mean square residual (RMR = 0.034) and PCLOSE value (0.067) also point to a well-fitting model. Lower Akaike information criterion (AIC) and expected cross-validation index (ECVI) values compared with alternative models indicate strong predictive capacity. Finally, Hoelter's critical N values (218/194) exceed 200, suggesting that the sample size is sufficient to yield stable parameter estimates. These diagnostics collectively affirm that the hypothesized model is robust and offers a plausible explanation of the relationships among variables.

Extended discussion: Implications for theory and practice

The findings have several theoretical implications. First, by demonstrating that decision-making quality partially mediates the effect of AI adoption on HRM effectiveness, the study extends classic technology adoption models (TAM and TOE) which focus mainly on adoption intentions and perceived usefulness. Here, adoption translates into outcomes primarily via an intermediate process—decision quality. This suggests that technology adoption research should pay greater attention to process improvements rather than treating adoption as an end in itself. Second, integrating socio-technical and ethical governance perspectives underscores that AI's benefits are realized only when technological capabilities are aligned with social systems and governed responsibly. This aligns with calls from STS scholars for designing technology within its organizational and cultural context (Trist & Bam forth, 1951; Thomas, 2024). Third, the strong moderating role of ethical governance highlights that AI adoption can lead to divergent outcomes depending on governance practices, supporting the view that technology is not inherently good or bad but shaped by human values and systems. For practitioners, the study identifies practical levers for effective AI deployment in HRM. One of the most important recommendations is to priorities training and digital literacy among HR staff. Many respondents felt underprepared to use AI tools, which could undermine adoption efforts. Organizations should invest in capacity building to ensure that HR professionals can interpret AI outputs, ask critical questions and integrate data insights into practice. Another recommendation is to develop transparent governance frameworks. Clear guidelines on data usage, privacy protection, algorithmic auditing and employee communication can build trust and acceptance of AI systems. Establishing cross-functional ethics committees and including diverse stakeholders in system design and evaluation will further strengthen governance. The findings also underscore the importance of aligning AI initiatives with strategic HR goals. AI should not be implemented in isolation or for novelty's sake; rather, it should serve clear objectives such as improving recruitment quality, employee engagement or workforce planning. Finally, practitioners should recognize that AI adoption is a change management challenge. Communicating benefits, addressing fears of job displacement, and involving employees in the adoption process are crucial for success.

Broader contextualization: Lebanon and similar fragile economies

Lebanon's current context—characterized by economic crisis, political instability, infrastructural shortcomings and cultural specificities—raises unique questions about AI adoption. Economic instability means that organizations have limited resources to invest in sophisticated technology, yet AI offers cost-saving potential through automation and efficiency. However, erratic electricity supply and unreliable internet can disrupt AI systems. Political uncertainty undermines long-term planning and discourages large capital investments.

Regulatory gaps leave organizations without clear guidance on data protection and AI use, creating legal uncertainty. Cultural factors such as wasta—a network-based system of favors and influence—can conflict with algorithmic decision-making, which emphasizes merit and objectivity. The study suggests that AI may challenge these informal practices by imposing standardized and transparent criteria, but only if people trust the algorithms and see them as fair. Ethical governance can help build this trust by ensuring that AI decisions are explainable and auditable. Lebanon’s experience could thus inform other fragile economies facing similar challenges, offering a template for responsible AI adoption that balances innovation with cultural sensitivity and social equity.

Synthesis with global literature

The results contribute to a nuanced understanding of AI’s impact on HRM across contexts. In advanced economies, AI is sometimes portrayed as an inevitable progression towards data-driven HRM, with debates focusing on technical sophistication and labor displacement. In fragile contexts, adoption is slower but the stakes are different: AI offers a path to overcome inefficiencies and nepotism but also risks reinforcing power imbalances if misused. Comparatively, this study resonates with research from the Global South that emphasizes the dual nature of AI—as both an opportunity for leapfrogging and a potential tool of exploitation (ESCWA, 2024). Scholars like Rub-off (2019) warn that surveillance capitalism commodifies personal data and concentrates power in corporations. The Lebanese case illustrates that surveillance concerns are not limited to consumer data but extend to the workplace. HR analytics, if unregulated, could lead to intrusive monitoring and discrimination. This underscores the importance of embedding privacy and fairness protections in AI governance.

Comparative sectoral insights

Sectoral differences in AI adoption and governance were not the primary focus of our analysis, but they merit discussion because they reflect broader institutional dynamics. Private sector firms, especially multinational subsidiaries and large Lebanese corporations, are often early adopters of AI due to competitive pressures and access to resources. They may adopt AI to streamline recruitment, reduce labor costs and manage large workforces. However, without sufficient governance, these firms risk public backlash if AI decisions are perceived as discriminatory. Academic institutions, accounting for a quarter of our sample, serve as both adopters and incubators of AI expertise. Universities may use AI to manage faculty recruitment, admissions or administrative tasks. They also house research programmes that could support evidence-based AI governance. Non-governmental organizations (NGOs) face unique incentives: donor funding may require digital innovation, but resource constraints and ethical commitments may push NGOs to adopt AI cautiously. They may be pioneers in developing context-appropriate governance models. Public sector organizations have the least exposure to AI and often operate under legacy systems. Yet public sector HRM can benefit immensely from AI in recruitment, deployment and performance evaluation. For public bodies, trust and transparency are paramount; any perceived misuse of AI could erode public confidence in government. Tailoring AI adoption strategies to sectoral realities is therefore essential.

Policy recommendations for organizations

Based on the findings, several policy recommendations emerge for organizations seeking to implement AI in HRM responsibly:

Develop a comprehensive AI strategy that aligns with organizational goals and values. This strategy should outline clear objectives for AI adoption, identify priority areas (e.g., recruitment, training, performance management), allocate resources for infrastructure and training, and set measurable KPIs for evaluating impact.

Establish a multidisciplinary AI governance committee comprising HR professionals, IT specialists, legal advisors, ethics scholars and employee representatives. This committee should oversee AI procurement, implementation, auditing and communication. It should ensure that AI systems comply with local laws and global ethical standards, maintain records of data sources and algorithms, and conduct regular bias and impact assessments.

Invest in staff capacity and digital literacy by providing targeted training on AI concepts, data interpretation, algorithmic bias and ethical considerations. HR professionals should be empowered to understand how AI tools generate recommendations, recognize potential biases and challenge automated outputs when necessary. Training should also cover data protection and privacy regulations.

Promote transparency and employee engagement by communicating openly about AI use in HR processes. Employees should know when AI is involved in decisions, what data is collected, how it is used and how they can appeal or provide feedback. Transparent communication builds trust and reduces anxiety about AI-driven surveillance or job displacement.

Enhance data quality and integration by ensuring that HR data are accurate, complete and compatible across systems. Poor data quality can undermine AI performance, produce biased recommendations and erode confidence. Organizations should audit data sources, eliminate outdated or irrelevant fields, and standardize data formats across departments.

Pilot AI tools and adopt a phased implementation. Instead of a big-bang approach, organizations should test AI applications in limited contexts, gather feedback, assess outcomes and refine systems before scaling up. Pilot projects can reveal context-specific challenges, such as cultural resistance or technical glitches, that must be addressed.

Monitor and evaluate AI systems continuously. Governance should not end once a system is deployed. Organizations should track AI performance, evaluate fairness and accuracy, and update models as conditions change. Regular evaluations should involve diverse stakeholders, including employees, to identify unintended consequences and adjust policies accordingly.

Policy recommendations for government and regulators

The role of government in shaping the AI landscape is especially important in fragile economies where legal and institutional frameworks are incomplete. Lebanese policymakers and regulators could consider the following measures:

Draft comprehensive AI regulations that address data protection, privacy, algorithmic accountability and transparency. These laws should clarify employer responsibilities, employee rights and mechanisms for redress in cases of discrimination or harm caused by AI decisions. Regulations should be developed in consultation with employers, employees, civil society and academic experts to ensure relevance and enforceability.

Encourage industry standards and certification schemes for AI in HRM. Government agencies, in collaboration with professional associations, could create certifications for AI tools that meet fairness and transparency criteria. Certified systems would give organizations confidence that they are using ethically vetted technologies.

Support research and capacity building through funding for universities and research institutions to study AI ethics, develop local expertise and create context-specific guidelines. Scholarship programmes and continuing education courses could train future HR leaders and technologists in responsible AI use.

Foster public–private partnerships to share best practices, develop pilot projects and disseminate knowledge. Government ministries could partner with private firms and NGOs to implement AI in public sector HRM, test governance frameworks and scale successful approaches across sectors.

Safeguard digital infrastructure by investing in reliable electricity, broadband connectivity and cybersecurity. Without basic infrastructure, AI systems cannot function consistently, and data may be vulnerable to breaches. National digital transformation initiatives should priorities infrastructure alongside ethical frameworks.

Establish national AI ethics boards or ombudsman offices to oversee the use of AI across sectors, handle complaints and conduct independent audits. Such bodies could set guidelines, evaluate compliance and sanction organizations that misuse AI. A central authority can ensure consistency and provide support to smaller organizations with limited governance capacity.

Expanding on limitations and opportunities for further research

The cross-sectional design of this study restricts our ability to infer causality. Longitudinal studies could explore how AI adoption trajectories evolve and whether improvements in decision quality and HRM effectiveness are sustained over time. Longitudinal research could also examine learning curves—do organizations become more effective at using AI as they gain experience, and does ethical governance mature with time? Another limitation is the reliance on self-reported perceptions, which may not perfectly reflect actual AI usage or effectiveness. Mixed-methods research could triangulate surveys with objective metrics, such as recruitment cycle times, employee turnover rates or performance scores. Interviews and ethnographic studies could capture employee experiences, particularly for groups who may feel marginalized by algorithmic decisions.

This study focused on Lebanese organizations; cross-country comparisons could identify cultural and institutional factors that influence AI adoption and governance. For instance, a comparative study of Lebanon and Jordan might reveal how different regulatory environments and cultural norms affect AI's impact on HRM. Similarly, sector-specific studies could explore AI in health care, education or manufacturing HRM, where roles and risks differ. Future research could also test interventions—for example, training programmed or governance frameworks—to evaluate what measures best promote ethical and effective AI adoption. Finally, while this study measured decision-making quality at an organizational level, there is scope to explore individual-level outcomes, such as employee satisfaction, trust in management or perceptions of justice when AI is used in HR decisions.

Final remarks

In conclusion, this expanded analysis underscores the complexity and promise of AI adoption in HRM within fragile economies. The interplay between technological innovation and ethical governance shapes whether AI acts as a tool for empowerment or a source of harm. Lebanon's case illustrates that even in contexts of political and economic instability, organizations can harness AI to improve HR decision-making and effectiveness—provided that they invest in governance, training and transparency. Scholars and practitioners alike must remain vigilant to the ethical challenges of AI while embracing its potential to transform work in equitable and resilient ways.

Theoretical and Practical Contributions

Theoretically, this research extends the technology acceptance and socio-technical systems frameworks by incorporating decision-making quality as a mediator and ethical governance as a moderator in the AI–HRM relationship. It provides empirical validation of how ethical practices amplify the effectiveness of AI adoption in HR processes. Practically, it offers a roadmap for organizations in fragile contexts to harness AI responsibly—balancing efficiency with fairness and human judgment. The study thus enriches both scholarly discourse and managerial practice on AI-enabled HRM in developing economies.