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Article

ARTIFICIAL INTELLIGENCE-DRIVEN HUMAN RESOURCE MANAGEMENT AND EMPLOYEE JOB PERFORMANCE IN THE UAE PUBLIC SECTOR: THE MEDIATING ROLE OF INNOVATION

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Abstract: Artificial intelligence (AI) is increasingly embedded in human resource management (HRM), yet its performance consequences depend on whether employees perceive AI-enabled HR systems as fair, transparent, privacy-protective, and trustworthy. We examine the direct effects of four AI-HRM dimensions—algorithmic fairness (bias mitigation), transparency, privacy protection, and trust—on employee job performance and test innovation as a mediating mechanism in the United Arab Emirates (UAE) public sector. Guided by the Resource-Based View, we administered a cross-sectional survey to employees of Dubai Municipality. Of 382 returned questionnaires, 376 valid responses were analyzed using SPSS and Partial Least Squares Structural Equation Modeling. Fairness, transparency, and privacy produced statistically significant direct coefficients, but the effects were negligible in magnitude: fairness and transparency were negative, privacy was positive, and trust was nonsignificant. Innovation generated substantially larger indirect effects from fairness and transparency, with transparency producing the dominant pathway ($\beta = .792$, $p < .001$). Fairness and transparency exhibited competitive mediation, privacy showed a direct-only effect, and trust showed negative indirect-only mediation. These findings indicate that AI-HRM creates performance value primarily when ethical and governance capabilities are converted into innovative work practices. Because the job-performance model reached the boundary value $R^2 = 1.000$ and the innovation-to-performance effect size was exceptionally large, we interpret the model-quality statistics cautiously and treat them as priorities for robustness re-estimation.
Keywords: AI-enabled HRM, employee job performance, innovation, algorithmic fairness, transparency, privacy, trust, UAE public sector

1. Introduction

Artificial intelligence has moved rapidly from an experimental analytics tool to an embedded component of human resource management. AI-enabled HR systems can screen applicants, support workforce planning, personalize learning, identify retention risks, assist performance appraisal, and automate routine employee services. These capabilities promise faster decisions, more consistent processes, and a shift of HR effort from administration toward strategic work (Tambe et al., 2019; Vrontis et al., 2022; Chowdhury et al., 2023). Reviews of AI-augmented HRM similarly show that value is produced when data, analytical capability, and managerial judgment are combined rather than when algorithms merely replace existing procedures (Prikshat et al., 2023; Pan & Froese, 2023; Nawaz et al., 2024).

The effect of AI on employee job performance, however, is not automatically positive. AI can improve task speed, decision quality, and access to feedback, but it can also reproduce historical bias, obscure the reasoning behind employment decisions, intensify monitoring, and create uncertainty about responsibility and job security. Employees evaluate not only whether an AI tool is technically useful but also whether its decisions are fair, understandable, secure, and dependable. These ethical and relational judgments influence acceptance, engagement, and the willingness to use AI-generated recommendations in daily work (Bankins et al., 2022; Hunkenschroer & Luetge, 2022; Chatterjee et al., 2022; Figueroa-Armijos et al., 2023).

These issues are particularly salient in the public sector. Government organizations must pursue efficiency while preserving accountability, procedural justice, citizen confidence, and employee rights. Their performance objectives are broader than financial outcomes and include service quality, regulatory compliance, responsiveness, and public value. The UAE provides an important context because national digital transformation and the UAE Artificial Intelligence Strategy 2031 have encouraged government entities to integrate AI into service delivery and

internal administration (UAE 2031, 2018). Research on the UAE indicates increasing use of AI in HR practices and continuing emphasis on knowledge management, innovative culture, and employee creativity in public organizations (Singh & Shaurya, 2021; Al Sayegh et al., 2023; Alosani & Al-Dhaafri, 2023; Al Hosani et al., 2023).

Despite this policy momentum, evidence on how specific characteristics of AI-enabled HRM affect individual job performance in the UAE public sector remains limited. Much of the literature examines AI adoption at a broad organizational level, focuses on private firms, or treats ethical concerns as implementation barriers rather than as performance-relevant capabilities. Studies also tend to analyze fairness, transparency, privacy, or trust separately. This fragmentation makes it difficult to determine which dimensions matter directly and which become valuable only when employees and managers use AI to create new processes, services, and ways of working.

Innovation may be the missing conversion mechanism. AI provides analytical capacity and automation, but innovation determines whether those capabilities are translated into redesigned workflows, improved decisions, creative problem solving, and better employee experiences. Innovation-based HR practices have been linked to employee satisfaction, creative behavior, organizational agility, and performance (Lasisi et al., 2020; Rubel et al., 2023; Al Daboub et al., 2024; AlMunthiri et al., 2024). From this perspective, ethical AI-HRM features do more than reduce risk: they create a climate in which employees can experiment with and learn from technology. Conversely, an AI system that is opaque, intrusive, or distrusted may suppress the innovative behaviors needed to realize its potential.

This study therefore examines the direct effects of algorithmic fairness, transparency, privacy protection, and trust in AI-enabled HRM on employee job performance and evaluates innovation as a mediator. The study makes three contributions. First, it uses the Resource-Based View (RBV) to conceptualize ethical AI-HRM characteristics and innovation as complementary organizational capabilities. Second, it provides evidence from a large public-sector organization in the UAE, a context underrepresented in AI-HRM research. Third, it separates direct effects from indirect innovation pathways, providing a more precise basis for managerial and policy decisions. The resulting model addresses not only whether AI-HRM affects performance, but how its value is generated. AI has progressed quickly from being an experimental analytics tool to becoming a part of HRM. HR systems with AI can filter out candidates, aid workforce planning, customize learning, spot retention risks, assist performance appraisals, and automate mundane employee tasks. These capabilities have the potential to streamline HR processes, reduce decision-making time, and free up HR professionals to focus on more strategic tasks (Tambe et al., 2019; Vrontis et al., 2022; Chowdhury et al., 2023). The findings of AI-enhanced HRM are also reviewed and it is found that value is created when data, analytical power, and managerial judgment are integrated instead of merely replacing the existing processes with algorithms (Prikshat et al., 2023; Pan & Froese, 2023; Nawaz et al., 2024).

AI's impact on employee performance is not necessarily beneficial, however. While AI can make tasks faster, better, and feedback more easily accessible, it can also perpetuate historical bias, remove the rationale behind employment decisions, increase monitoring, and cause uncertainty about responsibility and job security. Workers assess not only the technical usefulness of an AI tool but also its fairness, comprehensibility, security, and reliability in making decisions. These ethical and relational judgments impact their acceptance, engagement, and inclination to utilize AI-generated recommendations in their daily work (Bankins et al., 2022; Hunkenschroer & Luetge, 2022; Chatterjee et al., 2022; Figueroa-Armijos et al., 2023).

These issues are particularly salient in the public sector. Government organizations need to strive for efficiency while maintaining accountability, procedural justice, citizen confidence and employee rights. They have a wider range of performance targets than financial ones, such as service quality, regulatory compliance, responsiveness and public value. The UAE offers an important context since the UAE Artificial Intelligence Strategy 2031 and the national digital transformation have motivated government bodies to adopt AI in service provision and internal government operations (UAE 2031, 2018). The UAE studies revealed that AI is becoming more prevalent in HR practices, while knowledge management, innovative culture, and employee creativity continue to be significant factors in public organizations (Singh & Shaurya, 2021; Al Sayegh et al., 2023; Alosani & Al-Dhaafri, 2023; Al Hosani et al., 2023).

However, there is limited evidence regarding the impact of specific aspects of AI-powered HRM on individual job performance in the public sector in the UAE. Many of the studies have been conducted at an

organizational level, in private companies, or on the ethical aspects as a barrier to the implementation of AI, and not as a performance aspect. It is also the case that studies generally break down fairness, transparency, privacy, or trust into separate components. This fragmentation makes it hard to identify which dimensions are relevant in themselves and which are only useful when employees and managers leverage AI to develop new processes, services and ways of working.

The missing conversion mechanism could be innovation. While AI offers analytical power and automation, innovation is essential to ensure that these capabilities are translated into redesigned workflows, better decisions, creative problem solving, and enhanced employee experiences. HR practices based on innovation have been correlated with employee satisfaction, creative behaviour, organizational agility and performance (Lasisi et al., 2020; Rubel et al., 2023; Al Daboub et al., 2024; AlMunthiri et al., 2024). In this context, ethical AI-HRM capabilities are not just about minimizing risk but fostering an environment where employees can safely explore and learn from AI. On the other hand, if the AI system is opaque, intrusive, or not trusted, it can stifle innovative behaviors that are essential for achieving its potential.

This study thus explores the direct impact of algorithmic fairness, transparency, privacy protection and trust in AI-enabled HRM on employee job performance and how innovation serves as a mediator. The study makes three contributions. First, it uses the Resource-Based View (RBV) to conceptualize ethical AI-HRM characteristics and innovation as complementary organizational capabilities. Second, it offers insights from a large public-sector organization in the UAE, which is underrepresented in the field of AI-HRM. Third, it distinguishes between direct effects and indirect innovation pathways, which allows for a more precise basis for managerial and policy decisions. The model presented in this paper not only considers the impact of AI-HRM on performance but also how AI-HRM creates value.

2. Theoretical Background and Hypothesis Development

2.1 AI-Enabled HRM, Job Performance, and the Resource-Based View

Job performance is the behaviors and results that employees produce that help the organization achieve its goals. In today's technology-driven work environments, performance encompasses task completion, decision quality, adaptability, collaboration, and the ability to effectively leverage digital tools (Jiang et al., 2023). AI can impact these results by making information more accessible, minimizing HR admin, offering personalized feedback, and enabling HR decisions to be made in a more timely fashion. Empirical studies have found that AI usage is related to employee performance and work engagement, but the extent and direction of the relationships vary based on the quality of the implementation and leadership support (Tong et al., 2021; Wijayati et al., 2022; Chukwuka & Dibie, 2024).

According to the RBV, these resources and capabilities are valuable, rare, difficult to imitate, and well organized, which leads to sustained performance differences (Barney, 1991). Modern developments of the RBV focus on dynamic capabilities: organizations need to be constantly able to reconfigure resources with the evolution of technologies and environments (Helfat et al., 2023). AI infrastructure alone is not likely to achieve this as algorithms and software can be bought or copied. Rather, competitive and performance value stems from how organizations control AI, integrate it with human expertise, and integrate it into unique routines. Studies using the RBV for AI also show that the capabilities of the organization will determine whether or not the investment in technology will lead to a better performance (Chen et al., 2022).

Algorithmic fairness, transparency, privacy protection and trust are considered as complementary AI-HRM capabilities in this study. They determine if AI is seen as a valid and viable tool for employees. Innovation is the organizational mechanism that re-combines these capabilities with employee knowledge and work practices. The model hence allows for the prediction of direct performance effects as well as indirect effects via innovation.

2.2 Algorithmic Fairness (Bias Mitigation) and Job Performance

AI systems learn from data and can perpetuate past recruitment, promotion, appraisal or development practices. Unrepresentative data, proxy variables, model design, or institutional practices in historical data records can lead to biased outputs (Peng et al., 2022; Varsha, 2023; Albaroudi et al., 2024). If employees feel that an AI-driven HR process is biased towards specific groups or lacks important context, procedural justice and trust in

performance management can be undermined. This can lead to decreased motivation, collaboration, and acceptance of AI feedback (Bankins et al., 2022).

We operationalized this construct in our questionnaire by positively worded items that determine if AI systems make fair decisions, treat employees equally, and reduce personal or cultural bias. Thus, we view the construct as perceived algorithmic fairness/bias mitigation. Performance should be supported by fair systems, which should enhance perceptions of justice, minimize defensive reactions, and allow workers to work without challenging decisions. Accordingly:

H1: Perceived algorithmic fairness (bias mitigation) in AI-enabled HRM positively influences employee job performance.

2.3 Transparency and Job Performance

Transparency refers to the degree to which employees grasp how AI is being used, the data it's analyzing, the standards it's applying, and the logic behind HR choices. In opaque systems, it's difficult for employees to figure out how to fix mistakes or how to do better. Clear and effectively communicated AI can lead to a greater sense of control, accountability, and acceptance, whereas "black box" systems can foster suspicion and resistance (Yanamala, 2023; Vorm & Combs, 2022). Disclosure also influences how AI feedback influences employee behavior, and it can be as important as the technology itself (Tong et al., 2021).

Transparent HR systems provide employees with actionable data on performance expectations, and enable managers to blend algorithmic data with contextual judgment. Transparency should be particularly relevant in the public sector where accountability and procedural clarity are institutional requirements. Therefore:

H2: Transparency in AI-enabled HRM positively influences employee job performance.

2.4 Privacy Protection and Job Performance

In many cases, AI-powered HRM systems depend on a vast amount of data about employees, such as their performance metrics, learning histories, communications, attendance, and behavioral data. These data can be used for personalized decisions, but can also be experienced as a feeling of surveillance and loss of autonomy. Employees' privacy concerns are heightened when they are unaware of what information is being gathered, how long it will be stored, who will have access to it, and if it will be used for purposes other than those stated (Chatterjee et al., 2022; Yanamala, 2023).

Good privacy protection can enhance psychological security and minimize distractions, stress and defensive behaviour. When employees feel their data is secure, they are more inclined to interact with digital systems and enter accurate data, leading to better data quality for AI-driven decisions. Thus, privacy protection is not just a compliance issue; it's an organizational capability that safeguards the human capital that AI relies on. Thus:

H3: Perceived privacy protection in AI-enabled HRM positively influences employee job performance.

2.5 Trust in AI-Enabled HRM and Job Performance

Trust is the employees' confidence in the AI systems and the organization that uses them. It is influenced by perceived competence, reliability, fairness, benevolence and accountability. In HRM, trust plays a crucial role, as AI suggestions can impact hiring, assessment, compensation, and training. Studies indicate that ethical perceptions, performance expectancy, and social influence have an impact on trust in AI-based recruitment and HR systems (Hmoud & Várallyai, 2020; Figueroa-Armijos et al., 2023; Arora & Mittal, 2024).

If employees trust the AI tools, they should be more inclined to use recommendations, share pertinent information, and incorporate technology into everyday decisions. Low trust can result in avoidance, workarounds, or superficial compliance. AI adoption studies are also associated with psychological contracts and employee engagement (Braganza et al., 2021). Hence:

H4: Trust in AI-enabled HRM positively influences employee job performance.

2.6 The Mediating Role of Innovation

Innovation is the development, application and realization of a new idea, process, tool or service that enhances the activity of an organization. In HRM, innovation means changing the way recruitment, learning,

performance management, employee services, and workforce planning are done by finding new mixes of technology and human skills. The HR practices that foster innovation boost employee empowerment, experimentation and the utilization of knowledge to improve performance (Lasisi et al., 2020; Rubel et al., 2023; Al Daboub et al., 2024). The UAE public sector also highlights the critical role of innovative culture, employee creative behavior, and organizational agility in service performance (Alosani & Al-Dhaafri, 2023; Al Hosani et al., 2023; Almazrouei et al., 2024).

It is anticipated that innovation will serve as a mediator between AI-HRM and performance as AI usually generates possibilities and not performance per se. Predictive analytics might show that there is a skills gap, for instance, but innovative HR design is necessary to develop a learning pathway that is targeted. Although automated employee services can save time on transactions, innovation is required to restructure roles and redirect saved time to higher value activities. Generative or analytical tools can provide suggestions, but it is up to the employees to experiment, adapt, and incorporate them into context-specific workflows. Such a logic is aligned with the findings of AI capability being a framework that needs to be translated into organizational practices (Chowdhury et al., 2023; Pan & Froese, 2023) and with evidence that there is a connection between AI-related innovation and satisfaction and performance (Gayathri & Bella, 2024).

Fairness can foster innovation because it can help to build psychological safety and confidence that experimentation will be judged fairly. Transparency enables employees to grasp the functionality of AI and the creative applications it can have. Protection of privacy can help to alleviate fears of monitoring and encourage open participation. Trust can lead to greater openness to discovering what AI can do and suggesting new uses. Hence, the impact of each dimension of AI-HRM is expected to be carried forward to job performance through innovation.

H5: Innovation mediates the relationship between algorithmic fairness (bias mitigation) and employee job performance.

H6: Innovation mediates the relationship between AI transparency and employee job performance.

H7: Innovation mediates the relationship between privacy protection and employee job performance.

H8: Innovation mediates the relationship between trust in AI-enabled HRM and employee job performance.

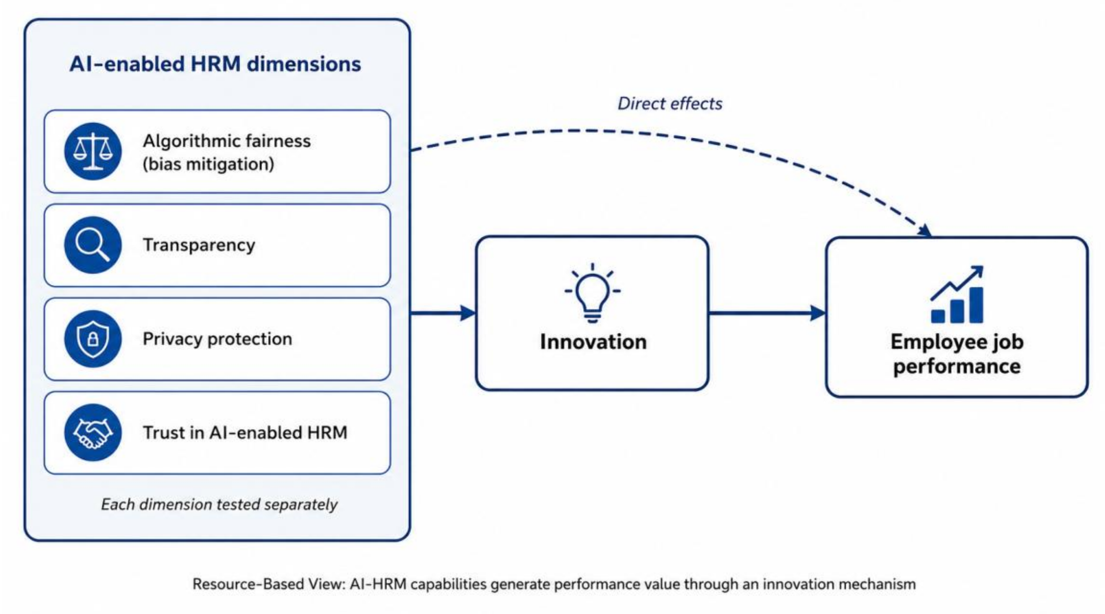

Figure 1: Conceptual model of AI-enabled HRM, innovation, and employee job performance

Note. Solid arrows represent the mediated pathway through innovation; the dashed arrow represents the direct effects of each AI-HRM dimension on employee job performance. Each AI-HRM dimension was estimated as a separate construct.

3. Methodology

3.1 Research Design and Setting

A quantitative, cross-sectional, explanatory survey design was used as the research aimed to estimate the relationships between latent constructs and test direct and mediated effects using standardized questionnaire data (Creswell, 2013; Saunders et al., 2016). The empirical context was Dubai Municipality, a large public-sector organization in the UAE that has implemented digital and AI-assisted systems for administrative and HR-related tasks.

The population was about 11,000 employees. The organization was chosen because it offers a mature public-sector environment where employees face AI-powered HR practices and innovation initiatives. The unit of analysis was the individual employee.

3.2 Sampling and Data Collection

A simple random sampling method was employed to send out an online questionnaire to employees and functional levels. The target sample size was determined by the Krejcie and Morgan sample-size table for a population of about 11,000, with a target size of 376. A priori G*Power calculation showed that the achieved sample was sufficient for the proposed analysis as the calculation resulted in a minimum of 129 cases for four predictors at a medium effect size.

A total of 382 questionnaires were returned and 376 were used after screening, which is 98.43% of the questionnaires returned. The online version enabled employees to respond as they wished and minimized interviewer effect.

3.3 Measures

Demographic questions were included in our questionnaire, as were 30 substantive items on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Five items were used for each construct initially. The AI-HRM dimensions were algorithmic fairness/bias mitigation, transparency, privacy protection, and trust. Innovation and employee job performance were modeled as the mediator and dependent variable, respectively.

Algorithmic fairness items evaluated the impartiality, equal treatment, and low level of discrimination in AI-assisted HR decisions, as well as the reduction of personal and cultural bias. Transparency items measured organizational explanation of the use of AI, communication of evaluation criteria, intelligibility of decision processes, and openness about the role of AI. Privacy items included secure handling of personal information, respect for employee privacy, protection of personal data, and clarity of data-use policies. Trust items related to the fairness, accuracy, reliability, and employee orientation of AI-powered HR processes. Innovation items included encouragement of new ideas, development of creative solutions, support for innovative thinking and ongoing exploration of new applications of AI. Job-performance items measured meeting expectations, quality improvement, efficiency, motivation, decision quality, and perceived performance improvements from AI in HRM.

We used the items from existing AI-HRM, innovation and employee-performance scales (Albaroudi et al., 2024; Yanamala, 2023; Chatterjee et al., 2022; Braganza et al., 2021; Al Daboub et al., 2024; Chukwuka and Dibie, 2024). In the measurement-model assessment, one fairness item (BIA5) was dropped due to low loading, resulting in 4 indicators of fairness.

3.4 Data Analysis

Data were screened, described and preliminary reliability analysis was performed using SPSS. Distributional properties were examined using skewness and kurtosis, while variance inflation factors (VIFs) were used to check for multicollinearity. Next, we estimated the hypothesized model using Partial Least Squares (PLS) Structural Equation Modeling (SEM) with SmartPLS software (Ringle et al., 2015). PLS-SEM was chosen due to the prediction-oriented research, the presence of multiple latent constructs and mediation paths, and the examination of a developing research model (Hair et al., 2022).

Indicator loadings, internal consistency, convergent validity and discriminant validity were used to assess the measurement model. Path coefficients, t statistics, p values, indirect effects, explained variance, effect sizes, and

predictive relevance were used to evaluate the structural model. A p value of < .05 was considered statistically significant.

4. Results

4.1 Sample Characteristics and Preliminary Diagnostics

We retained 376 usable responses from the 382 questionnaires returned, yielding a 98.43% usable-response proportion. The largest age category was 31–40 years (27.93%), followed by 41–50 years (23.14%). Men represented 78.19% of the sample, 58.24% of respondents held a bachelor's degree, and the largest experience category was 6–10 years (28.46%). The sample therefore provides substantial organizational coverage, although its male concentration and single-organization setting should be considered when interpreting generalizability.

Skewness and kurtosis values for all items were between −3 and +3 and indicator VIF values ranged between 1.406 and 2.841. These results suggest acceptable distributional behavior and the absence of serious item-level multicollinearity based on the thresholds adopted. Item ranged from 3.809 to 4.511, with most of the responses falling in the high to very high range. The overall positive trend indicates high employee ratings for the AI-HRM practices, innovation, and performance measured, while the clustering of scores at the higher end of the spectrum may indicate a potential ceiling effect, which could limit the ability to distinguish between highly similar constructs.

Table 1: Respondent profile (N = 376)

Variable	Category	n	%
Age	21–30	75	19.95
	31–40	105	27.93
	41–50	87	23.14
	51–60	73	19.41
	Above 60	36	9.57
Gender	Male	294	78.19
	Female	82	21.81
Highest education	Certificate	19	5.05
	Diploma	68	18.09
	Bachelor's degree	219	58.24
	Master's degree	54	14.36
	Doctoral degree	16	4.26
Work experience	0–5 years	49	13.03
	6–10 years	107	28.46
	11–15 years	79	21.01
	16–20 years	76	20.21
	Above 20 years	65	17.29

4.2 Measurement Model: Reliability and Validity

After deletion of the low-loading BIA5 item, the retained indicator loadings ranged from .610 to .870, with most at or above .70. Cronbach's alpha values ranged from .793 to .864 and composite reliability values ranged from .797 to .888. These coefficients provide clear evidence of acceptable internal consistency across the six constructs and justify proceeding to structural-path assessment.

Table 2: Measurement-model reliability

Construct	Retained items	Cronbach's α	Composite reliability
Algorithmic fairness (bias mitigation)	4	.805	.827
Transparency	5	.813	.822
Privacy protection	5	.806	.847
Trust in AI-enabled HRM	5	.864	.888
Innovation	5	.793	.799

Employee job performance	5	.793	.797

Note. The measurement-model summary yielded α = .793 for employee job performance, whereas the preliminary reliability analysis yielded α = .783. Both values exceed .70 and support acceptable internal consistency; the small difference is treated as an output discrepancy to be reconciled in the robustness re-estimation.

We assessed convergent and discriminant validity using average variance extracted (AVE), the Fornell–Larcker criterion, and cross-loadings. There are some inconsistencies in the summary AVE values and some loadings estimates vary between the outer-loading and cross-loading outputs. Thus, we consider the evidence of reliability as acceptable while the evidence of construct-validity as provisional until the measurement model is re-estimated and reconciled. This distinction is crucial because good structural conclusions should be based on good constructs that are reliable and clearly different.

4.3 Direct Structural Effects

The findings of our direct-effect results do not indicate that ethical AI-HRM dimensions are always positively associated with employee job performance. Only one of the constructs (privacy protection) had a statistically significant coefficient in the hypothesized positive direction ($\beta = .005$, $t = 2.343$, $p = .020$). Algorithmic fairness had a significant negative coefficient ($\beta = -.007$, $t = 2.982$, $p = .003$) and transparency had a larger significant negative coefficient ($\beta = -.017$, $t = 4.183$, $p < .001$). Trust was not significant ($\beta = .001$, $t = .938$, $p = .349$). Thus, H3 was supported, H4 was not supported and H1 and H2 were not supported because the signs observed were opposite the predicted positive direction.

Note that statistical significance is not the same as practical size. The four direct coefficients were very small ($|\beta| \le .017$). Therefore, the direct routes alone do not account for much substantive change in job performance even if the p values are < .05. The central analytical question is thus not whether fairness or transparency has a direct impact, but whether these dimensions lead to organizational conditions that enable innovation to lead to better performance.

Table 3: Direct and indirect hypothesis tests

Hyp.	Path	β	t	p	Decision
H1	Fairness → Job performance	−.007	2.982	.003	Not supported as hypothesized; significant negative
H2	Transparency → Job performance	−.017	4.183	<.001	Not supported as hypothesized; significant negative
H3	Privacy → Job performance	.005	2.343	.020	Supported; significant positive
H4	Trust → Job performance	.001	.938	.349	Not supported
H5	Fairness → Innovation →	.242	9.155	<.001	Supported mediation

	Job performance				
H6	Transparency → Innovation → Job performance	.792	29.068	<.001	Supported mediation
H7	Privacy → Innovation → Job performance	.052	1.361	.174	Not supported
H8	Trust → Innovation → Job performance	−.064	2.313	.021	Supported; negative indirect effect

Note. Coefficients are based on the bootstrapped hypothesis tests. Minor numerical differences between the tabular results and the structural-model diagram are treated as rounding or transcription discrepancies and should be resolved in the robustness re-estimation.

4.4 Mediation and Total-Effect Interpretation

The interpretation of the structural model was revolutionized by innovation. The indirect effects of fairness ($\beta = .242$, $t = 9.155$, $p < .001$), transparency ($\beta = .792$, $t = 29.068$, $p < .001$), and trust ($\beta = -.064$, $t = 2.313$, $p = .021$) were significant, whereas the privacy indirect effect was not ($\beta = .052$, $t = 1.361$, $p = .174$). The mediated pathway

of transparency was the largest, with a coefficient that was over three times the fairness indirect effect and much larger than each of the direct coefficients in the model.

The sign of the direct and indirect paths indicate four different mechanisms. Competitive, or inconsistent, mediation was found for fairness and transparency, which had relatively small negative direct effects, but relatively large positive innovation pathways, resulting in approximate total effects of .235 and .775, respectively. The pattern for Privacy was direct-only since the positive direct path was significant and the indirect path was not. The indirect-only mediation of trust was negative due to the non-significant direct path and the significant and negative path mediated by innovation. The trust result is interpreted with caution since it is not expected and may be due to suppression or model-specification effects.

Table 4: Analytical classification of the mediation results

Dimension	Direct β (p)	Indirect β (p)	Analytical conclusion
Fairness	−.007 (.003)	.242 (<.001)	Competitive mediation; approximate total β = .235. Performance value is realized mainly through innovation.
Transparency	−.017 (<.001)	.792 (<.001)	Competitive mediation; approximate total β = .775. This is the dominant pathway in the model.

Privacy	.005 (.020)	.052 (.174)	Direct-only effect; approximate total β = .057, but the mediated component is not statistically reliable.
Trust	.001 (.349)	−.064 (.021)	Negative indirect-only mediation; approximate total β = −.063. The unexpected direction warrants robustness testing.

Overall result. The strongest defensible conclusion is therefore that innovation—not a simple direct technology effect—is the principal transmission mechanism linking AI-enabled HRM to employee job performance. In particular, transparency appears valuable when it enables employees to understand, adapt, and redesign work around AI rather than when it is treated as disclosure alone.

4.5 Explanatory Power and Model-Diagnostic Caution

The result of our analysis showed that the R2 for innovation was .907 which means that the four dimensions of AI-HRM collectively account for a very high proportion of variance in the mediator. It also produced $Q^2 = .489$ for innovation and $Q^2 = .541$ for job performance, which were both greater than zero based on the blindfolding criterion employed in this study. These statistics are indicative of good in-sample explanatory and predictive power of the estimated model.

The job-performance R2, however, is exactly 1.000 and the output for the effect-size is f2 = 720.545 for the innovation-to-performance relationship. These boundary and extreme values are not valid indicators of a flawless behavioral model, but are warning signs of possible duplicated indicators, overlapping construct scores, coding errors or transcription errors. This concern is corroborated by the same order of the descriptive means for the five innovation items and the five job-performance items.

Robustness interpretation. We thus offer the path-level pattern as the main empirical finding, and are not claiming the model to be perfectly predictive. The dataset, item assignments, latent-variable specifications, bootstrapping output, AVE calculations, R^2 values and effect sizes all need to be re-estimated for complete robustness. These claims of perfect explanatory power, exceptional goodness of fit, or near-deterministic prediction are withheld until that re-estimation is done.

5. Discussion

5.1 Direct Effects of AI-Enabled HRM Dimensions

The most obvious conclusion is that the effects of AI on HRM performance are indirect. All of the direct coefficients were very small and only the privacy factor was in the expected positive direction. The mediation results for fairness and transparency were competitive, for privacy, direct-only mediation was found, and for trust, negative indirect-only mediation was found. So, the model does not make a simple statement that responsible AI attributes lead to individual output. It demonstrates rather that fairness and transparency are useful primarily as they facilitate innovation, learning and work redesign.

This fairness finding is in line with the literature that demonstrates how employees react to algorithmic decisions via justice perceptions (Bankins et al., 2022). The fair system can help to minimise resistance and increase the willingness of employees to engage in change through technology. The negative direct coefficient might be due to a statistical suppression effect as both AI-HRM dimensions and innovation were included simultaneously. It can also mean that fairness safeguards can be added to a process without necessarily boosting output, and that production steps or careful review can be added to a process without necessarily boosting output. However, when innovation is taken into account, the total effect is positive, reinforcing the overall thesis that bias mitigation is about protecting and mobilizing human capital, and not just speeding up work.

Transparency had the largest overall influence, as its small negative direct effect was more than offset by its large positive indirect effect. Transparency can be initially cognitively and procedurally costly as employees take time to grasp explanations, criteria, and governance processes. However, with that knowledge, it is possible to modify tools, question incorrect outputs and create new applications. This aligns with studies that have found that explainability and disclosure are associated with acceptance and productive interaction with intelligent systems (Vorm & Combs, 2022; Tong et al., 2021). Transparency also helps to make innovation more legitimate and easier to scale in a public organization, as it helps to hold people accountable.

There was a small positive direct effect of privacy protection with no significant innovation pathway. This discovery indicates that privacy is more of a protection for concentration, autonomy and psychological security. While privacy protection alone might not encourage experimentation or idea generation, staff might work better if they know that their personal information is safe. The finding is consistent with privacy-calculus studies that indicate that privacy issues influence intentions to use HR analytics (Chatterjee et al., 2022). Therefore, privacy should be considered as a precondition, instead of an innovation driver.

Performance was not directly predicted by trust, consistent with the notion that trust may be a threshold variable. Baseline trust in the public sector technology could be relatively high, which decreases the variance and the explanatory power. The important negative indirect effect via innovation is counterintuitive and needs to be interpreted with caution. This could be a sign that people are not encouraged to experiment with AI tools and solutions, or it could be suppression of correlated constructs. Calibrated trust, with understanding, oversight and questioning of outputs, can be more valuable than generalised trust. This distinction is in line with research that highlights the interplay of transparency, trust and acceptance (Vorm & Combs, 2022).

5.2 Innovation as the Performance-Conversion Mechanism

The main contribution of the study is the mediation results. Innovation was the only significant pathway from trust to job performance and was the only pathway where fairness and transparency had an impact. These findings confirm the RBV argument that technology-related resources can only create value when they are organized and recombined in a firm-specific way. The information and automation AI systems provide can lead to redesigned processes, new services, better decisions and new roles for work.

The greatest indirect effect was found with transparency. You cannot creatively tweak a system that you don't understand. Explanations of data, criteria, limitations, and decision logic provide the knowledge needed to identify new use cases and integrate AI with professional judgment. There was also a significant indirect impact of fairness, suggesting that when employees believe that their ideas and performance are being treated fairly, they are more inclined to act innovatively. These findings corroborate the findings of other studies that relate innovation based HR practices to creative behaviour and organizational performance (Lasisi et al., 2020; Rubel et al., 2023; Al Daboub et al., 2024).

Without privacy mediation, the difference between enabling and protecting mechanisms is reinforced. There is a greater harm reduction and direct functioning with privacy, and greater information and psychological conditions for experimentation with transparency and fairness. The trust result indicates that the benefits of innovation are not only related to the amount of trust, but also to its quality. Managers should foster informed trust – trust based on proven reliability, explain ability, employee involvement and human oversight.

This conversion mechanism is of strategic importance in the UAE public sector. While national digital initiatives can help speed up technology deployment, it is local learning, employee participation and redesign of public services that are necessary to drive organizational performance. So, innovation isn't a byproduct of AI adoption; it is how AI adoption becomes performance.

6. Contributions and Implications

6.1 Theoretical Contributions

First, the study builds on the RBV of AI by considering ethical AI-HRM characteristics as organizational capabilities instead of as a compliance problem. Fairness, transparency, privacy, and trust are key factors in determining whether employees can use AI as a valuable resource. This puts focus on governance and human interpretation of technology instead of technical adoption.

Secondly, the model suggests that innovation serves as a mediator between AI-HRM resources and employee performance. The opposing direct and indirect impacts of fairness and transparency highlight why research solely focused on direct impacts might underestimate or misrepresent the value of AI in organizations. It's not just about whether AI is ethical or trusted; it's about whether those attributes can empower workers to reimagine work.

Third, the study distinguishes between ethical aspects. The direct effect was on privacy, and the predominant effect of transparency and fairness was via innovation. Trust did not have a direct pathway and had a negative indirect pathway. These differences suggest not to view responsible AI as a monolithic construct.

Fourth, the UAE public sector evidence contributes to the geographical and institutional diversity of AI-HRM research. Public organizations are a potentially informative context for the study of ethical AI capabilities, as they have strong digital-transformation mandates, as well as high levels of accountability and workforce diversity.

6.2 Managerial and Policy Implications

Responsible AI governance should be a performance system, not just a risk-control exercise, for public-sector leaders. Fairness audits should be done both prior to and following deployment, based on representative data, documented criteria, and human review of high impact decisions. There needs to be a way for employees to challenge results, fix data and appeal decisions. These practices ensure procedural justice and engender trust for innovative use.

Transparency should be action oriented. Just technical documentation is not enough. HR departments should provide an overview of the system, the data it relies on, how recommendations are made, its shortcomings, and where human judgment still plays a crucial role. Transparency can be transformed into learning and experimentation with role-specific dashboards, plain language explanations, AI literacy training, and examples of appropriate and inappropriate use.

There must be clear boundaries that are enforced to protect privacy. Organizations should limit data collection, specify retention periods, only give access to what is needed, explain lawful purposes, and separate data used for development or analytics from employment decisions as appropriate. Staff to be made aware of monitoring and consent procedures. Since privacy has a direct impact on performance, failure in this area can directly impact concentration, morale and engagement.

Trust building efforts must be designed to build calibrated trust, not passive trust. All staff should be involved in design, pilot testing, evaluation and continuous improvement. Consequential HR decisions should be human-in-the-loop. Performance metrics should include AI adoption rates, as well as error correction, employee understanding, appeal outcomes, and quality of human oversight.

Lastly, AI deployment should be coupled with a clear innovation strategy. Public organisations can create cross-functional innovation teams, provide protected experimentation periods, set up internal sandboxes, peer learning communities, and recognition for responsible AI-driven improvements. Training should be a mix of technical skills, process redesign, ethics and change management. This is in line with the evidence that innovative culture and employee creativity are the main factors that affect the performance of the UAE public sector (Alosani & Al-Dhaafri, 2023; Al Hosani et al., 2023).

7. Limitations and Future Research

There are a number of limitations to the study. It is a cross-sectional design which does not allow for causality in time. Longitudinal studies should be conducted to investigate the changes in employee perceptions as AI systems mature and users become more experienced. Field experiments might be used to evaluate the

effectiveness of different governance mechanisms (e.g., explanation formats, fairness audits, privacy controls) in driving innovation and performance.

Data was self-reported and gathered from one public sector organization in UAE. This could result in common method variance and social-desirability bias. In the future, employee surveys should be used in conjunction with supervisor ratings, objective performance measures, system-use logs, audit results, and qualitative interviews. Generalizability would be enhanced by replication at the federal level, at the municipal level, by private companies, and by other countries.

In our instrument, it was called “bias” but it was actually about fair treatment and the lack of bias. Future applications should implement unambiguous construct names and differentiate between distributive, procedural and interactional fairness. Trust should also be broken down into trust in the technology, trust in the organization, and trust in human oversight. Perceived surveillance, control of data, consent and security are ways of modeling privacy.

The mediator of innovation was considered as one. Future research should differentiate between process innovation, service innovation, innovative work behavior and between exploratory and exploitative innovation. Additional pathways may be explained by other mechanisms such as AI literacy, psychological safety, job autonomy, perceived organizational support, learning orientation and employee well-being. Moderators like role type, nationality, age, technical proficiency and exposure to AI should also be analyzed.

Finally, a robustness audit of the data and the SmartPLS specification is required to reconcile the coefficients, the model-quality statistics and the labels. Re-estimation using the study data would help to increase confidence in the very strong indirect effects and the unusually small direct coefficients.

8. Conclusion

This study investigated the relationship between four aspects of AI in HRM (algorithmic fairness, transparency, privacy and trust) and employee job performance in the UAE public sector and the role of innovation in explaining these relationships. The direct effects were small in size, as privacy was positive, fairness and transparency were negative and trust was not significant based on 376 valid responses and the estimated PLS-SEM paths. Fairness and transparency, however, had significant impacts on innovation, and transparency had the strongest impact. Thus, the evidence indicates that there is an innovation-conversion explanation for the performance of AI-HRM, not a direct-effect explanation of AI-HRM performance.

The results indicate that ethical governance and innovation of AI should not be treated as separate agendas. Fairness and transparency add value when they facilitate employees' understanding of AI, push back on inappropriate AI outputs, take risks with AI experimentation, and redesign work. Trust is calibrated through reliability, participation and meaningful human oversight, whereas privacy protects performance directly by creating secure boundaries. Until measurement and structural models are re-estimated and harmonized, including the job-performance $R^2 = 1.000$ and the extreme values of the effect sizes, these conclusions are provisional.

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