

Responsible AI-Enabled Human Resource Management and Employee Innovative Work Behavior in Jordanian Commercial Banks: The Mediating Role of Employee Trust in Artificial Intelligence

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Abstract

This study examines the relationship between the Responsible AI-Enabled Human Resource Management (RAI-HRM) and the employee innovative work behavior in the Jordanian commercial banks, and it examines whether the employee trust in artificial intelligence (AI) mediates this relationship. The study draws on the social exchange theory, where the responsible use of AI in the HR function is considered as a signal of the fair treatment from the organization, which is reciprocated by the employees through the trust and the innovative behavior. The RAI-HRM was conceptualized as a higher-order construct that consists of six dimensions, which are AI transparency, AI explainability, AI fairness, data privacy and security, human oversight, and accountability. The survey data were collected from 249 bank employees, and the data were analyzed by using the partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4, with the embedded two-stage approach for the higher-order construct. The RAI-HRM was positively and strongly associated with the employee trust in AI ($\beta = 0.917$, $p < 0.001$), and the employee trust in AI was positively associated with the innovative work behavior ($\beta = 0.900$, $p < 0.001$). Moreover, the indirect effect of the RAI-HRM on the innovative work behavior through the trust in AI was significant ($\beta = 0.825$, $p < 0.001$). The model explained 84.1% of the variance in the trust in AI and 81.0% of the variance in the innovative work behavior. The study is one of the few studies that measure the responsible AI in HRM as an integrated multidimensional construct in a real organizational setting in an Arab banking context. The findings suggest that the way in which AI is governed in HR, rather than the adoption of AI itself, is associated with the level of the employee trust and with the use of AI for the innovation. However, the results are based on cross-sectional and single-source data, and therefore the possible common method variance should be taken into consideration when the results are interpreted.

Keywords: Responsible AI-Enabled Human Resource Management; Employee Trust in Artificial Intelligence; Employee Innovative Work Behavior; Social Exchange Theory; PLS-SEM; Jordanian Commercial Banks

1. Introduction

Artificial intelligence (AI) is increasingly transforming the way in which the organizations design and implement the human resource management (HRM). The AI-based applications are now used in the recruitment, the employee selection, the performance evaluation, the talent management, the workforce planning, the training, and the employee analytics. In the same direction, the human resources information systems and the digital HR transformation were examined as tools for enhancing the organizational creativity and the organizational effectiveness (Aloqaily, 2022; Alrousan et al., 2025), and the upskilling of the employees was discussed as a condition for working with AI (Jaiswal et al., 2022). Moreover, the AI-based applications are not limited to the HR function, since they are also used in the customs and the tax administrations (Shubailat et al., 2024b, 2024c; Alseikh et al., 2026; Qahman et al., 2026), in the education (Qahman et al., 2025), and in the transformation of the global finance (Thosony, 2026). These applications enable the organizations to process large volumes of data and to automate the routine activities, and they also improve the speed of the decision-making. However, the growing use of AI in HRM changes also the relationship between the employees, the managers, and the organizational systems, because the employees are no longer affected only by the human decision-makers, and they are increasingly affected by the algorithmic recommendations and the automated decisions (Budhwar et al., 2023; Malik et al., 2023). Accordingly, the integration of AI into HRM should not be evaluated only in terms of the efficiency and the cost reduction, and it must also be assessed according to its effect on the employee rights, the fairness, the privacy, and the dignity. The AI-based HR systems may reproduce the existing bias in the training data, and they may make decisions that the employees cannot understand or may collect a sensitive personal information about the employees. Moreover, the previous studies indicate that the adoption of AI does not lead automatically to positive employee outcomes, and the AI adoption should be understood as a socio-technical transformation rather than as a simple installation of a new digital tool (Makarius et al., 2020; Qamar et al., 2021; Singh & Pandey, 2024). In this context, Einola and Khoreva (2023) described the coexistence of the humans and AI in the workplace as an evolving relationship that affects the beliefs, the emotions, and the behavior of the employees.

The problem is particularly important in the banking sector. The banks process highly sensitive financial and personal information, and they operate under strict requirements that relate to the security, the compliance, and the accountability. In the Jordanian context, the previous researches highlighted the legal and cybersecurity challenges of integrating AI in the financial institutions (Alazzam et al., 2026), and they showed that the digital capabilities are increasingly associated with the banking performance (Altaamneh et al., 2026). In addition, the FinTech adoption was examined in relation to the financial performance of the Jordanian banks (Alhadab et al., 2025), and the FinTech was discussed as a channel for promoting the financial inclusion in the emerging economies (Mousa & Maabreh, 2024; Saroito, 2025), where the users evaluate also the transaction costs of the FinTech services (H. Zhao et al., 2024). Regarding the human resources in the same sector, Aloqaily (2023) examined the role of the HRM practices on the talent management in the Jordanian commercial banks. At the same time, the Jordanian commercial banks operate in a rapidly changing environment that is characterized by the digital banking, the FinTech competition, and the regulatory pressures, and in such environment the banks need employees who generate new ideas, promote them, and implement them in practice. Moreover, such environment requires the strategic intelligence, the effective decision-making and the strategic flexibility (Hamour et al., 2023), and the organizations in the

region continued to search for the competitive advantage after the COVID-19 pandemic (Al-Zaqeba et al., 2022).

Despite this importance, three gaps can be identified in the literature. First, the previous studies focused mostly on the AI adoption, the AI capability, or the technical effectiveness of the algorithms, while fewer studies examined the transparency, the explainability, the fairness, the data privacy, the human oversight, and the accountability together as one integrated construct. In the same line, the review of Bujold et al. (2024) showed that many studies on the responsible AI in HRM were based on hypothetical scenarios rather than real organizational contexts. Second, the psychological mechanism through which the responsible AI practices are related to the employee innovative work behavior is still not clear, and the mediating role of the employee trust in AI was insufficiently investigated. Third, the empirical evidence from Jordan and other Arab countries is limited, and especially from the banking sector.

Based on the above, the aim of the current study is to examine the relationship between the Responsible AI-Enabled Human Resource Management (RAI-HRM) and the Employee Innovative Work Behavior (EIWB) in the Jordanian commercial banks, with a particular attention to the mediating role of the Employee Trust in Artificial Intelligence (ETAI). More specifically, the study seeks to answer the following questions: (1) Is the RAI-HRM positively related to the employee trust in AI? (2) Is the employee trust in AI positively related to the innovative work behavior? (3) Does the employee trust in AI transmit the effect of the RAI-HRM on the innovative work behavior? The social exchange theory (Blau, 1964; Cropanzano & Mitchell, 2005) is used as the underpinning theory to explain these relationships.

The study is expected to contribute to the literature in three ways. First, it extends the research on the AI-enabled HRM beyond the adoption and the efficiency, and it conceptualizes and measures the RAI-HRM as a higher-order construct with six dimensions. Second, it applies the social exchange theory to the context of the AI-enabled HRM, and it proposes the employee trust in AI as the exchange mechanism that links the responsible governance of AI with the innovative work behavior of the employees. Third, it provides empirical evidence from the Jordanian commercial banks, which is a context where the evidence on the responsible AI in HRM is still limited. The remainder of the paper is organized as follows: Section 2 presents the theoretical background, Section 3 develops the hypotheses, Section 4 describes the methods, Section 5 reports the results, Section 6 discusses the findings, and Section 7 concludes the study.

2. Theoretical Background

2.1 Social Exchange Theory

The social exchange theory proposes that the relationships between the employees and the organization are based on the exchange of resources, and that the favorable treatment from one party creates an obligation for the other party to reciprocate (Blau, 1964). According to Cropanzano and Mitchell (2005), the exchange relationships develop over time into trusting and committed relationships when the parties follow the rules of the reciprocity, and the fair treatment is one of the main resources that the organization can provide to the employees. It is worth mentioning that the trust has a central place in this theory, because the employee who contributes to the organization beyond the formal requirements must trust that this contribution will be recognized and that the organization will not exploit it.

In the context of the current study, the responsible use of AI in the HR function can be considered as a form of the favorable treatment from the bank. When the bank explains how the AI systems work, protects the data of the employees, ensures a fair treatment, and keeps the humans responsible for the sensitive decisions, the employees may interpret these practices

as a sign that the bank respects their interests. Accordingly, the employees are expected to respond by developing a trust in the AI systems that are used by the bank, and then by reciprocating through the discretionary behaviors that benefit the bank. The innovative work behavior is considered as such discretionary behavior, because it is usually not included in the formal job description and it involves an extra effort and a personal risk (Janssen, 2000). Therefore, the social exchange theory provides one coherent logic for all the relationships in the proposed model.

2.2 Responsible AI-Enabled Human Resource Management

The RAI-HRM refers to the use of AI in the HR activities while maintaining the transparency, the explainability, the fairness, the data privacy and security, the human oversight, and the accountability. Unlike the conventional AI-enabled HRM, which emphasizes mainly the efficiency, the speed, and the automation, the RAI-HRM considers also the rights, the perceptions, and the psychological responses of the employees. Bankins (2021) developed an ethical decision-making framework for AI in HRM, and the framework emphasized that the appropriateness of the automation depends on the sensitivity of the HR task and on the potential consequences for the employees. Similarly, Votto et al. (2021) found that AI can improve the HR forecasting and the employee analytics, but it may also create risks that relate to the surveillance, the discrimination, and the privacy. In addition, the HRM practices were examined as drivers of wider organizational outcomes in Jordan, such as the total quality management (Ababneh et al., 2024) and the green sustainable performance (Aloqaily et al., 2024), and this indicates that the way in which the HR function is managed has consequences beyond the HR department.

Several systematic reviews confirmed the multidimensional nature of the AI-enabled HRM. Vrontis et al. (2022) explained that AI and the advanced technologies are transforming the traditional HR functions, while creating at the same time concerns about the job displacement and the dehumanization of the work. Gélinas et al. (2022) identified the legal and ethical issues as a distinct dimension of the AI-HRM, and Chowdhury et al. (2023) argued that the organizations need the technological, the human, and the organizational AI capabilities in order to obtain value from AI. In addition, Dima et al. (2024) reported that AI changes the roles of the HR professionals, the line managers, and the employees. The most comprehensive review was provided by Bujold et al. (2024), who reviewed 107 empirical studies and identified six areas of the responsible AI in HRM, which are the bias and discrimination, the perceived justice and trust, the privacy, the explainability and transparency, the role of humans, and the responsible implementation. Moreover, the authors found that the system accountability and the employee autonomy were insufficiently examined.

Based on these reviews, the current study conceptualizes the RAI-HRM through six dimensions. The AI transparency and the AI explainability relate to the extent to which the employees know what data are collected and how the system reaches its decisions. The AI fairness relates to the extent to which the system does not discriminate against the individuals on the basis of the gender, the age, or other personal characteristics (Delecraz et al., 2022; Lavanchy et al., 2023). The data privacy and security relate to the protection of the sensitive information of the employees, while the human oversight and the accountability relate to the existence of human professionals who review the AI outputs and who are responsible for the final decisions (Bankins, 2021; Bujold et al., 2024). It is worth mentioning that the digital technologies such as the blockchain were also examined as tools for enhancing the governance and the risk management in Jordan (Jebril et al., 2024; Shubailat et al., 2024a), and this supports the view that the governance mechanisms are a necessary part of any digital system. It should be noted that the findings about the transparency are not completely consistent, because an

excessive or a poorly presented information may increase the confusion of the employees. Therefore, the transparency in this study is understood not only as a technical disclosure, but also as understandable explanations together with clear procedures for the human review and the correction.

2.3 Employee Trust in Artificial Intelligence

The trust is defined as the willingness of a party to be vulnerable to the actions of another party, based on the expectation that the other party will perform an action that is important to the trustor (Mayer et al., 1995). Accordingly, the employee trust in AI refers to the willingness of the employee to rely on the AI system and on its recommendations despite the uncertainty and the potential vulnerability. Glikson and Woolley (2020) reviewed the empirical research on the human trust in AI, and they explained that the trust is influenced by the characteristics of the technology, the user, and the organizational context, and that the trust is not determined by the technical accuracy alone. In a similar way, the behavioral studies examined the attitudes, the subjective norms and the perceived behavioral control as determinants of the compliance behavior of the individuals (Al-Zaqeba & Al-Rashdan, 2020), and this confirms that the psychological states of the individuals are important for explaining their behavior toward the organizational and the institutional systems.

Moreover, Choung et al. (2023) distinguished between the functionality-related trust, which concerns the competence and the reliability of AI, and the human-like trust, which concerns the integrity, the benevolence, and the concern for the human well-being. In the same direction, Gkinko and Elbanna (2023) identified the cognitive, emotional, and organizational forms of the employee trust in the conversational AI, where the organizational trust reflects the confidence in the intentions and the governance of the organization. These distinctions are relevant to HRM, because the employees may trust an AI system in performing the calculations while they distrust the same system in the sensitive decisions such as the promotion or the performance evaluation. It is important to distinguish between the RAI-HRM and the employee trust in AI: the RAI-HRM refers to the perceived governance practices of the organization, while the employee trust in AI refers to the psychological state of the employee, which is the willingness to rely on the AI system.

2.4 Employee Innovative Work Behavior

The employee innovative work behavior refers to the intentional generation, promotion, and implementation of new ideas within the work role, the group, or the organization (Janssen, 2000). The innovative work behavior is broader than the creativity, because it includes not only the producing of an idea, but also the communicating of the idea to others and the transforming of the idea into a practical solution. AI may support the innovative work behavior by automating the routine tasks, improving the access to the information, and providing the employees with additional cognitive resources. In this regard, Mikalef and Gupta (2021) found that the organizational AI capability contributes to the organizational creativity and the firm performance, and Li et al. (2022) reported that the AI capability improves the organizational creativity through the knowledge sharing and the organizational cohesion. Furthermore, Jia et al. (2024) argued that AI augments the employee creativity when it complements rather than replaces the human capabilities, and this is especially when the employees keep the responsibility for the interpretation and the judgment. Moreover, Alzeyoudi and Inezeh (2025) examined the impact of AI on the innovation in the UAE and the moderating role of the digital infrastructure, and Shubailat et al. (2025) examined the relationship between the family

connectedness and the entrepreneurial intentions, and these studies indicate that the innovation depends also on the context in which the individuals work.

3. Hypothesis Development

3.1 Responsible AI-Enabled Human Resource Management and Employee Trust in Artificial Intelligence

According to the social exchange theory, the employees evaluate the treatment they receive from the organization, and the fair and respectful treatment increases their trust in the organization and in its systems (Cropanzano & Mitchell, 2005). When the employees understand how the AI system uses their data and how its decisions are generated, they are more likely to perceive the system as predictable and legitimate. Bujold et al. (2024) identified the transparency, the explainability, the perceived justice, the privacy, and the human involvement as central principles of the responsible AI in HRM, and Glikson and Woolley (2020) explained that the trust in AI depends on the reliability, the transparency, and the predictability of the system.

Moreover, the fairness is an important condition for the trust in AI. Lavanchy et al. (2023) found that the applicants perceived the fully algorithmic recruitment procedures as less fair than the human-led or the human-assisted procedures, and this effect continued even when the outcome was favorable for the applicants. This finding indicates that the responsible AI requires more than the technical accuracy, and it requires also the human participation and the opportunities to challenge the decisions. In the banking context, the employees deal every day with sensitive financial and personal information, and therefore they may be especially attentive to the way in which the bank protects their own data and ensures the accountability of the AI-supported decisions. Accordingly, when the employees perceive the AI-enabled HR practices as transparent, explainable, fair, secure, supervised by humans, and supported by clear accountability, they are expected to develop a greater trust in the AI systems. Therefore, the following hypothesis is proposed:

H1: Responsible AI-Enabled Human Resource Management is positively related to Employee Trust in Artificial Intelligence.

3.2 Employee Trust in Artificial Intelligence and Employee Innovative Work Behavior

The innovation requires the employees to generate new ideas, to promote them, and to implement them in the practice, and these activities involve normally the uncertainty, the experimentation, and the possibility of the failure. From the perspective of the social exchange theory, the employees who trust the systems of the organization are more willing to invest an extra effort and to take the personal risks that are associated with the innovation (Cropanzano & Mitchell, 2005). In contrast, the employees who do not trust AI may avoid using it for the innovative tasks, because they question the accuracy of its outputs or they fear that their information may be misused.

The recent empirical evidence supports this relationship. Liu et al. (2026) found that the employees who trust AI are more likely to perceive it as a collaborative job resource, and this perception is associated with a higher innovative behavior. Similarly, Lin et al. (2026) found that the trust in AI can support the digital innovation, although the excessive trust may produce an automation bias and may reduce the critical monitoring of the AI outputs by the employees. In addition, Prasad and De (2024) showed that the trust operates as a psychological mechanism through which the perceptions of the generative AI are related to the employee outcomes. Based on these arguments, the employees who trust AI are expected to be more willing to use

it in generating, promoting, and implementing new ideas. Accordingly, the following hypothesis is proposed:

H2: Employee Trust in Artificial Intelligence is positively related to Employee Innovative Work Behavior.

3.3 Responsible AI-Enabled Human Resource Management and Employee Innovative Work Behavior

The RAI-HRM may be related to the innovative work behavior because it provides the employees with information, timely feedback, learning opportunities, and analytical support, and it allows them to focus in the problem-solving and the creative work instead of the repetitive administrative activities. The empirical studies support the existence of an overall positive relationship between AI and the innovation. Sweiss and Yamin (2024) found that the AI-enabled HR practices were associated with the task satisfaction and the creative willingness of the employees, and Zhang et al. (2025) found that the AI usage was positively associated with the innovation behavior at work, although the openness and the job complexity influenced the strength of this relationship. Nevertheless, Tong et al. (2021) showed that the reactions of the employees to the AI feedback may vary depending on how the involvement of AI is disclosed, and this suggests that the way in which AI is governed and communicated is an important condition for the positive outcomes.

From the perspective of the social exchange theory, the responsible practices of the bank represent a favorable treatment that the employees tend to reciprocate through the discretionary behaviors, and the innovative work behavior is one of these behaviors. However, the social exchange theory suggests also that this reciprocation occurs mainly through the development of the trust (Blau, 1964). For this reason, the current study does not propose an additional direct path beyond the trust, and it hypothesizes instead that the RAI-HRM has a positive overall (total) effect on the innovative work behavior, where this total effect is theorized to operate through the employee trust in AI. Therefore, the following hypothesis is proposed:

H3: Responsible AI-Enabled Human Resource Management has a positive total effect on Employee Innovative Work Behavior.

3.4 The Mediating Role of Employee Trust in Artificial Intelligence

The previous arguments suggest that the employee trust in AI is the mechanism that links the RAI-HRM with the innovative work behavior. According to the social exchange theory, the favorable treatment from the organization is first converted into the trust, and the trust then motivates the employees to reciprocate through the behaviors that benefit the organization (Blau, 1964; Cropanzano & Mitchell, 2005). In the context of the AI-enabled HRM, the employees are unlikely to use AI constructively if they perceive it as inaccurate, unfair, or intrusive. The responsible practices can reduce these concerns by explaining how AI works, protecting the employee data, ensuring a fair treatment, and maintaining the human responsibility for the important decisions, and these conditions increase the employee trust, which in turn encourages the employees to use AI in the innovative activities.

The previous research provides an initial support for this mechanism. Prasad and De (2024) found that the trust partially mediated the relationship between the perceptions of the generative AI and the organizational commitment, and Gkinko and Elbanna (2023) showed that the trust is formed through the perceptions of the AI competence, the organizational

intentions, and the quality of the human-AI interaction. Moreover, Liu et al. (2026) showed that the trust in AI contributes to the innovative behavior by enabling the employees to perceive AI as a job resource. It should be noted that the mediating mechanisms were also examined in the digital transformation research in the region, for example the tax awareness between the digital transformation and the sustainable tax compliance (Al-Omari et al., 2025), and the tax avoidance between the earnings management and the financial performance (Maabreh et al., 2026). Accordingly, the employee trust in AI is expected to transmit the positive effect of the RAI-HRM on the innovative work behavior. Therefore, the following hypothesis is proposed:

H4: Employee Trust in Artificial Intelligence mediates the relationship between Responsible AI-Enabled Human Resource Management and Employee Innovative Work Behavior.

Figure 1 presents the conceptual framework of the study, which summarizes the four hypotheses.

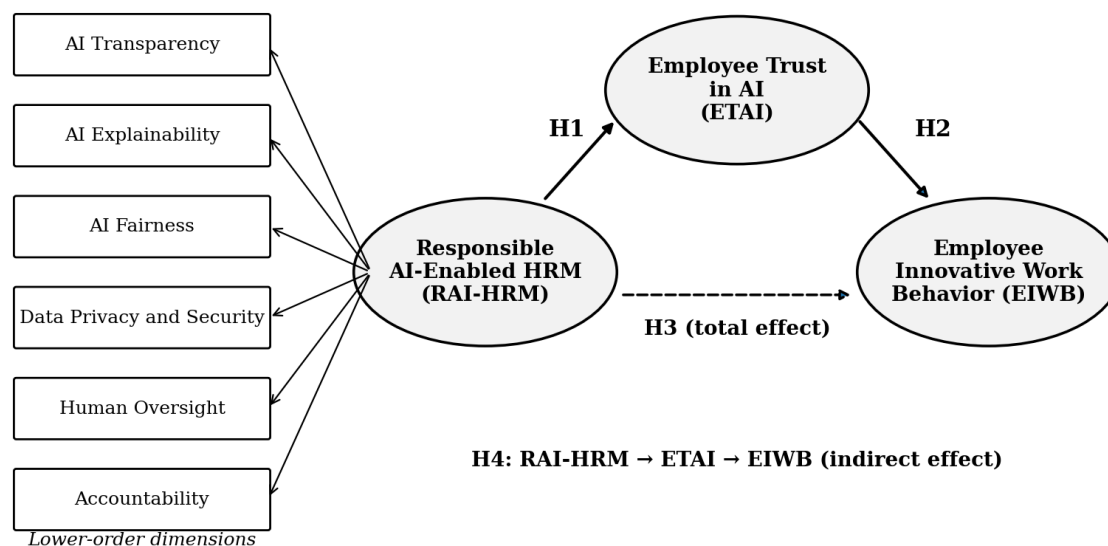


Figure 1. Conceptual framework of the study

4. Methods

The current study adopted a quantitative and cross-sectional research design in order to examine the relationships between the RAI-HRM, the employee trust in AI, and the employee innovative work behavior in the Jordanian commercial banks. The quantitative approach was appropriate because the study aimed to measure the perceptions of the employees by using structured questionnaire items and to test statistically the proposed relationships among the latent variables. The cross-sectional design enabled the researchers to collect the data from the bank employees at one point in time, and accordingly the findings should be interpreted as an evidence of the statistical associations rather than definitive causal effects.

The Partial Least Squares Structural Equation Modeling (PLS-SEM) was used through SmartPLS 4 in order to analyze the proposed model. The PLS-SEM was selected because the model includes a higher-order construct with six dimensions and a mediating variable, and because the PLS-SEM is appropriate for the prediction-oriented research and for the models that include complex relationships (Hair et al., 2022; Sarstedt et al., 2022).

4.1 Population, Sample, and Data Collection

The population of the study consisted of the employees who work in the Jordanian commercial banks. The bank employees were selected because they are directly affected by the digital transformation, the AI-supported decision-making, the electronic HR systems, and the performance analytics, and therefore their perceptions are important for evaluating whether AI is implemented in a responsible manner.

The data were collected through a structured questionnaire that was distributed to the employees of 9 Jordanian commercial banks. The adequacy of the sample size was assessed by a statistical power analysis. In the research model, each endogenous construct is predicted by a single construct, and for a medium effect size ($f^2 = 0.15$), a significance level of 0.05, and a statistical power of 0.80, the minimum required sample is 55 respondents (Faul et al., 2009). Therefore, the final sample of 249 respondents exceeds this requirement, and it satisfies also the minimum sample size guidelines that are commonly applied in the PLS-SEM (Hair et al., 2022).

The questionnaire targeted the employees who had experience with the organizational HR procedures and the digital systems in their banks. Where the employees had a direct or an indirect experience with the AI-supported HR activities.

4.2 Research Instrument

The questionnaire consisted of two sections. The first section collected the demographic and work-related information, which includes the gender, the age, the educational qualification, the years of experience, the job position, the managerial level, and the previous experience with AI. The second section measured the study constructs by using statements that were assessed on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The measurement items were modified in order to suit the context of the AI-enabled HRM in the banking sector. The RAI-HRM was measured through six dimensions, which are the AI transparency, the AI explainability, the AI fairness, the data privacy and security, the human oversight, and the accountability, and each dimension was measured with four items. The employee trust in AI was measured with 13 items that reflect the perceptions of the employees about the accuracy, the reliability, the fairness, the security, the transparency, and the dependability of the AI systems that are used or supported by the bank. It should be noted that the RAI-HRM items refer to the governance practices of the bank, while the trust items refer to the confidence of the employee in the AI system itself, although the two constructs share some common content such as the fairness and the transparency. The employee innovative work behavior was measured with nine items that cover the three stages of the innovation, which are the idea generation, the idea promotion, and the idea implementation (Janssen, 2000). Because the three stages are highly interrelated in the practice, the innovative work behavior was modeled as a unidimensional construct, and this is consistent with the approach of Janssen (2000).

4.3 Measurement Model

The RAI-HRM was specified as a reflective-reflective higher-order construct that consists of six lower-order dimensions. The reflective specification was adopted because the six dimensions are considered as manifestations of one common underlying orientation of the bank toward the responsible governance of AI, and it is expected that the change in this orientation is reflected at the same time in all the dimensions, which are therefore expected to be highly correlated (Sarstedt et al., 2019). The higher-order construct was estimated by using the

embedded two-stage approach (Sarstedt et al., 2019). In the first stage, the repeated-indicators approach was applied, in which all items of the six dimensions were assigned also to the higher-order construct, in order to obtain the latent variable scores of the dimensions. In the second stage, these latent variable scores were used as the indicators of the higher-order construct, and the structural model was estimated.

In both stages, the indicator reliability was examined through the outer loadings, where the values of 0.708 or above were considered satisfactory. The internal consistency reliability was assessed with the Cronbach's alpha and the composite reliability (ρ_a and ρ_c), where the values above 0.70 were considered acceptable, and the values above 0.95 were treated as a possible sign of the item redundancy (Hair et al., 2022). The convergent validity was assessed with the average variance extracted (AVE), where a value of at least 0.50 indicates that the construct explains at least half of the variance in its indicators.

The discriminant validity was assessed by using the heterotrait-monotrait ratio (HTMT), which provides a more reliable assessment than the traditional Fornell-Larcker criterion. The HTMT values below 0.85, or below 0.90 for the conceptually similar constructs, indicate that the constructs are empirically distinct, and in addition the bootstrapped confidence intervals of the HTMT were examined in order to check that they do not include the value of 1 (Henseler et al., 2015). A particular attention was given to the distinction between the RAI-HRM and the employee trust in AI, because the two constructs relate to the perceptions of the employees about AI. Moreover, the validity of the higher-order construct was evaluated in the second stage by examining the loadings of the six dimensions on the higher-order construct and their significance through the bootstrapping, together with the reliability and the AVE of the higher-order construct.

4.4 Structural Model

After the measurement model was established, the structural model was assessed in order to test the hypotheses. The structural model estimated the relationship between the RAI-HRM and the employee trust in AI (H1) and the relationship between the employee trust in AI and the innovative work behavior (H2). The total effect of the RAI-HRM on the innovative work behavior (H3) and the mediating role of the employee trust in AI (H4) were assessed as explained in Section 4.5.

The collinearity was examined by using the inner variance inflation factor (VIF). Because each endogenous construct in the model is predicted by only one construct, the inner VIF values are equal to 1.000, and therefore the collinearity is not a concern at the structural level. The significance of the relationships was assessed with the bootstrapping procedure in SmartPLS 4 (5,000 subsamples, two-tailed test), which generated the standard errors, the t-values, and the p-values, and the relationship was considered significant when $p < 0.05$ ($t > 1.96$).

The explanatory power of the model was assessed with the coefficient of determination (R^2). The effect size (f^2) was used in order to evaluate the contribution of each predictor, where the values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. The predictive power was assessed with the Q^2 -predict statistic that was obtained through the PLSpredict procedure, which evaluates the out-of-sample prediction, and the Q^2 -predict values above zero indicate that the model has a predictive relevance (Hair et al., 2022; Shmueli et al., 2019).

4.5 Mediation Analysis

In line with the social exchange theory and with the hypotheses developed in Section 3, the structural model specified the effect of the RAI-HRM on the innovative work behavior as

operating through the employee trust in AI. Accordingly, the specific indirect effect (RAI-HRM $\rightarrow$ ETAI $\rightarrow$ EIWB) was used to test H4, and the total effect of the RAI-HRM on the innovative work behavior was used to test H3. Because no direct path from the RAI-HRM to the innovative work behavior was included in the model, the total effect is equal to the indirect effect in this specification. The significance of the indirect effect was tested through the bootstrapping, which does not require the sampling distribution of the indirect effect to be normal (Hair et al., 2022). It should be noted that this specification does not allow the distinction between the partial and the full mediation (X. Zhao et al., 2010), and this point is discussed among the limitations of the study.

4.6 Data Screening and Common Method Considerations

Before conducting the PLS-SEM analysis, the data were examined for the incomplete responses, the abnormal response patterns (for example, the same answer for all items), the missing values, and the possible outliers. The responses with substantial missing information or with a clear evidence of the careless completion were excluded from the analysis, and the final dataset consisted of 249 usable responses. The demographic variables were collected in order to describe the sample, and they were not entered as control variables in the structural model, because the aim of the study was to test the theoretically specified relationships in a parsimonious model. Because the independent, mediating, and dependent variables were measured with the same questionnaire and were collected from the same respondents, the possibility of the common method bias was considered. The procedural remedies were applied by ensuring the anonymity of the respondents, stating that there were no right or wrong answers, and presenting the items in a clear and neutral wording (Podsakoff et al., 2003). Nevertheless, because all constructs were measured with a single instrument at one point in time, the common method variance cannot be completely ruled out, and this issue is acknowledged as a limitation of the study.

5. Results

This section reports the results of the respondent profile, the measurement model, and the structural model, in the same order in which the analysis was carried out. The interpretation of the results is presented in Section 6.

5.2 Measurement Model

The measurement model was assessed in two stages, following the embedded two-stage approach that is described in Section 4.3. Figure 2 shows the specification of the model, which includes the higher-order construct of the RAI-HRM with its six lower-order dimensions (AI explainability, AI fairness, AI transparency, data privacy and security, human oversight, and accountability), as well as the 13 indicators of the employee trust in AI and the nine indicators of the employee innovative work behavior that were retained in the final model.

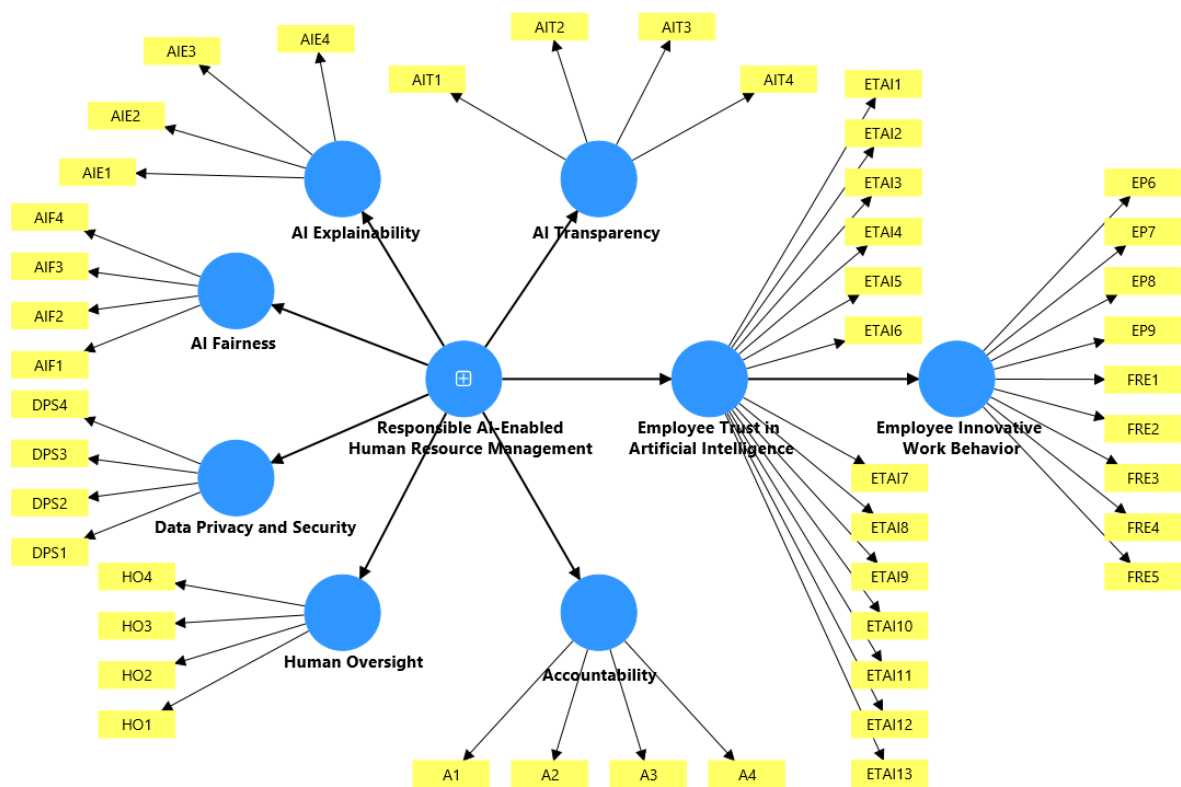


Figure 2. Measurement model with the higher-order construct of Responsible AI-Enabled Human Resource Management and its six lower-order dimensions

Figure 2 presents the first-stage estimation based on the repeated-indicators approach. The loadings of the items on the six lower-order dimensions ranged from 0.817 to 0.932, and the loadings of the items of the employee trust in AI and the innovative work behavior ranged from 0.750 to 0.913, and therefore all loadings exceeded the recommended threshold of 0.708. The R^2 values that are shown in Figure 3 belong to the first-stage estimation, and the final R^2 values of the structural model are reported in Table 5.

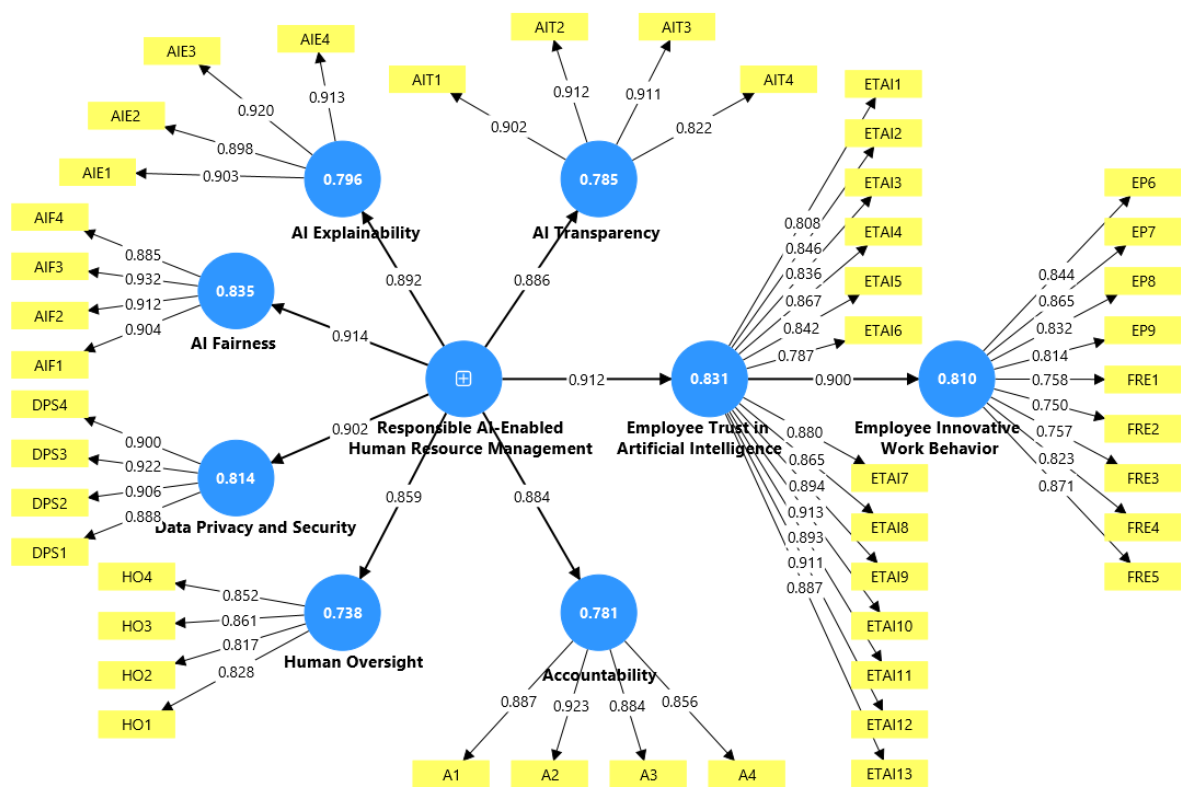


Figure 3. First-stage estimation of the measurement model (repeated-indicators approach): outer loadings and R² values

Table 3 reports the internal consistency reliability and the convergent validity of all constructs in the first stage. The Cronbach's alpha ranged from 0.861 (human oversight) to 0.976 (RAI-HRM), and the composite reliability (rho_c) ranged from 0.905 to 0.978, and all values are above the threshold of 0.70. The AVE values ranged from 0.631 (RAI-HRM) to 0.825 (AI explainability and AI fairness), which exceeds the minimum of 0.50. These results indicate a satisfactory reliability and convergent validity for all first-stage constructs. It should be noted that the reliability of the RAI-HRM in the first stage (Cronbach's alpha = 0.976) is above 0.95, and this is expected in the repeated-indicators approach, because the higher-order construct is measured in this stage by all the 24 items of its six dimensions.

Table 1. Internal consistency reliability and convergent validity of the constructs (first stage)

	Cronbach's alpha	Composite reliability (rho a)	Composite reliability (rho c)	Average variance extracted (AVE)
AI Explainability	0.929	0.930	0.950	0.825
AI Fairness	0.929	0.930	0.950	0.825
AI Transparency	0.910	0.914	0.937	0.788
Accountability	0.910	0.912	0.937	0.788
Data Privacy and Security	0.925	0.926	0.947	0.817
Employee Innovative Work Behavior	0.936	0.939	0.946	0.662
Employee Trust in Artificial Intelligence	0.972	0.972	0.975	0.748
Human Oversight	0.861	0.863	0.905	0.705
Responsible AI-Enabled Human Resource Management	0.976	0.977	0.978	0.631

Note: rho_a and rho_c are the two composite reliability coefficients reported by SmartPLS 4.

In the second stage, the latent variable scores of the six dimensions were used as the indicators of the RAI-HRM (Figure 4). The six dimensions loaded strongly on the higher-order construct, with loadings between 0.872 (human oversight) and 0.904 (AI fairness), and all loadings were significant ($p < 0.001$; see Figure 5). As shown in Table 3, the higher-order construct obtained a Cronbach's alpha of 0.948, a composite reliability (rho_c) of 0.958, and an AVE of 0.792, and these values confirm that the higher-order construct is well represented by its six dimensions. However, the reliability values of the employee trust in AI (Cronbach's alpha = 0.972; rho_c = 0.975) exceed 0.95, and this may indicate some redundancy among its 13 items (Hair et al., 2022).

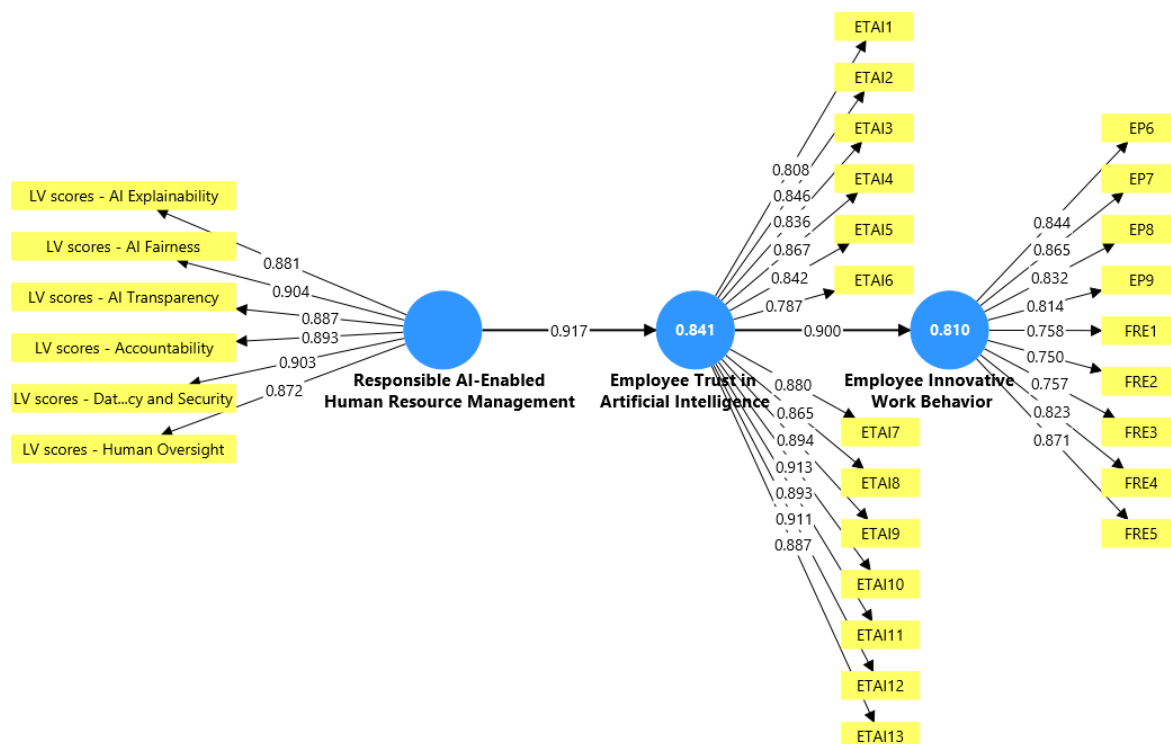


Figure 4. Second-stage model based on the latent variable scores of the six dimensions: outer loadings and R² values

Table 2. Reliability and convergent validity of the main constructs (second stage)

	Cronbach's alpha	Composite reliability (rho a)	Composite reliability (rho c)	Average variance extracted (AVE)
Employee Innovative Work Behavior	0.936	0.939	0.946	0.662
Employee Trust in Artificial Intelligence	0.972	0.972	0.975	0.748
Responsible AI-Enabled Human Resource Management	0.948	0.951	0.958	0.792

The discriminant validity was assessed with the HTMT criterion, and Table 4 reports the HTMT values among the three constructs of the second-stage model. Because the constructs are conceptually related, the values were evaluated against the threshold of 0.90, and the upper bounds of the bootstrapped confidence intervals were compared with the value of 1 (Henseler et al., 2015).

5.3 Structural Model

Because each endogenous construct is predicted by a single construct, the collinearity among the predictors does not arise in the structural model (inner VIF = 1.000). Table 5 summarizes the explanatory and the predictive power of the model.

Table 3. Explanatory power, effect size, and predictive relevance of the model

Endogenous construct	Predictor	R ²	Adjusted R ²	f ²	Q ² predict	RMSE	MAE
ETAI	RAI-HRM	0.841	0.841	5.288	0.841	0.402	0.299
EIWB	ETAI	0.810	0.810	4.268	0.904	0.312	0.242

Note: Q²predict, RMSE, and MAE were obtained through the PLSpredict procedure. RAI-HRM = Responsible AI-Enabled Human Resource Management; ETAI = Employee Trust in Artificial Intelligence; EIWB = Employee Innovative Work Behavior.

The RAI-HRM explained 84.1% of the variance in the employee trust in AI ($R^2 = 0.841$), and the employee trust in AI explained 81.0% of the variance in the innovative work behavior ($R^2 = 0.810$). The f^2 values of 5.288 (RAI-HRM $\rightarrow$ ETAI) and 4.268 (ETAI $\rightarrow$ EIWB) are far above the threshold of 0.35 for a large effect. In the PLSpredict procedure, both endogenous constructs obtained Q²predict values above zero (0.841 for the employee trust in AI and 0.904 for the innovative work behavior), and this indicates that the model has a predictive relevance. Figure 5 presents the estimated structural model with the path coefficients, the outer loadings, and the corresponding p-values.

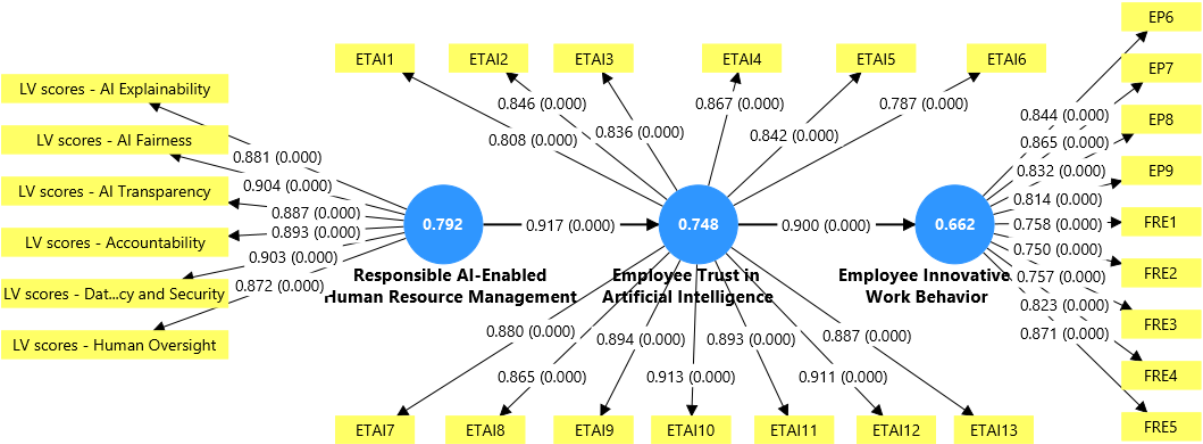


Figure 5. Structural model: standardized path coefficients and outer loadings, with p-values in parentheses (values inside the constructs are AVE values)

Table 4 reports the results of the hypothesis testing based on the bootstrapping procedure. The RAI-HRM was positively and significantly related to the employee trust in AI ($\beta = 0.917$, $t = 94.590$, $p < 0.001$), and therefore H1 is supported. The employee trust in AI was positively and significantly related to the innovative work behavior ($\beta = 0.900$, $t = 71.119$, $p < 0.001$), and therefore H2 is supported. The total effect of the RAI-HRM on the innovative work behavior was positive and significant ($\beta = 0.825$, $t = 42.473$, $p < 0.001$), and therefore H3 is supported. Because the model does not include a direct path from the RAI-HRM to the innovative work behavior, this total effect is carried entirely by the path through the employee trust in AI, and its value corresponds to the product of the two path coefficients ($0.917 \times 0.900 \approx 0.825$). Accordingly, the specific indirect effect through the employee trust in AI was significant ($\beta = 0.825$, $t = 42.473$, $p < 0.001$), and H4 is supported. It is worth mentioning that H3 and H4 are based on the same estimate in this specification, and therefore they should be read together as one evidence that the association between the RAI-HRM and the innovative work behavior is transmitted through the trust.

Table 4. Results of hypothesis testing

Hypothesis	Relationship	β (O)	Mean (M)	SD	t-value	P-value	Decision
H1	RAI-HRM $\rightarrow$ ETAI	0.917	0.917	0.010	94.590	0.000	Supported
H2	ETAI $\rightarrow$ EIWB	0.900	0.900	0.013	71.119	0.000	Supported
H3	RAI-HRM $\rightarrow$ EIWB (total effect)	0.825	0.826	0.019	42.473	0.000	Supported
H4	RAI-HRM $\rightarrow$ ETAI $\rightarrow$ EIWB (specific indirect effect)	0.825	0.826	0.019	42.473	0.000	Supported

Note: β (O) = original sample estimate; SD = standard deviation of the bootstrap distribution. A p-value of 0.000 indicates $p < 0.001$. Because the model contains no direct path from RAI-HRM to EIWB, the total effect (H3) equals the specific indirect effect (H4). RAI-HRM = Responsible AI-Enabled Human Resource Management; ETAI = Employee Trust in Artificial Intelligence; EIWB = Employee Innovative Work Behavior.

6. Discussion

The current study examined whether the responsible use of AI in HRM is associated with the trust of the employees in AI, and whether this trust is associated with the innovative work behavior among the employees of the Jordanian commercial banks. The results support the proposed model, and they describe a clear sequence which is consistent with the social exchange theory: when the employees perceive the AI-enabled HR practices as responsible, they report a higher trust in the AI systems, and this trust is associated with a greater willingness to generate, promote, and implement new ideas. The first finding is that the RAI-HRM was strongly and positively related to the employee trust in AI (H1). The employees who see the AI-supported HR processes as transparent, explainable, fair, secure, supervised by humans, and supported by clear accountability report a higher confidence in the AI systems that are used by their banks. This suggests that the trust is related to the way in which AI is governed rather than to its mere presence. The result supports the framework of Bujold et al. (2024), which identified the perceived justice and the trust as one of the central areas of the responsible AI in HRM, and the argument of Bankins (2021) that the ethical use of AI in HRM depends on keeping the human professionals responsible for the sensitive decisions. Moreover, the result is consistent with Glikson and Woolley (2020), who showed that the trust in AI depends on the reliability, the transparency, and the predictability. From the perspective of the social exchange theory, the responsible practices can be interpreted by the employees as a sign that the bank cares for their interests, and this interpretation strengthens their trust. The strength of the relationship may be explained partly by the banking context, because the bank employees handle sensitive information every day, and this may make them especially attentive to the security and the accountability, in line with the concerns that were reported by Alazzam et al. (2026).

The second finding is that the employee trust in AI was strongly and positively related to the innovative work behavior (H2). The innovation involves the uncertainty and the risk of the failure, and the employees who trust AI appear more willing to use it when they explore the problems, test the alternatives, and develop new work methods. This result is consistent with Liu et al. (2026), who found that the trust of the employees in AI is positively related to the innovative behavior, and with Gkinko and Elbanna (2023), who showed that the trust shapes

the way in which the employees engage with AI in the digital workplace. On the other hand, Lin et al. (2026) warned from the very high levels of trust, because they may lead to an automation bias and may reduce the critical monitoring of the AI outputs. Given the high path coefficient in this study, this warning deserves attention, and the goal for the banks should be a well-calibrated trust rather than an unconditional reliance on AI. In addition, an alternative explanation should be considered, because the employees who are more open to the new experiences may be more willing to trust new technologies and also more inclined to innovate, and therefore part of this relationship may reflect a shared disposition rather than an effect of the trust.

The third and fourth findings concern the total effect of the RAI-HRM on the innovative work behavior and the mediating role of the trust (H3 and H4). The total effect was positive and significant, and it was transmitted through the employee trust in AI, which supports the argument of the social exchange theory that the favorable treatment is reciprocated mainly after it is converted into the trust. The result is in line with Prasad and De (2024), who found that the trust mediated the relationship between the perceptions of the generative AI and the organizational commitment, and it extends their argument to the innovative behavior in the banking context. Furthermore, the result complements the studies which showed that the AI capability and the AI-enabled HR practices are associated with the creativity and the innovation (Li et al., 2022; Mikalef & Gupta, 2021; Sweiss & Yamin, 2024; Zhang et al., 2025), by identifying the trust as a mechanism through which such effects may occur. However, because the model did not include a direct path from the RAI-HRM to the innovative work behavior, the study cannot determine whether the responsible AI practices are related to the innovation also through other channels, such as the better access to the information and the feedback, and the findings of Tong et al. (2021) suggest that such channels are plausible.

Finally, the size of the relationships should be interpreted with a care. The path coefficients above 0.90 and the R^2 values above 0.80 are unusually high for the cross-sectional survey data. Two factors may contribute to this result. First, all constructs were measured with the same questionnaire from the same respondents at one point in time, and therefore the common method variance may have inflated the relationships. Second, the measure of the employee trust in AI includes the perceptions of the fairness, the security, and the transparency, which overlap conceptually with the dimensions of the RAI-HRM, and this overlap may have strengthened the observed association. For these reasons, the results are best read as an evidence of strong associations that are consistent with the proposed model, rather than as precise estimates of the causal effects.

7. Conclusion

The current study examined the relationship between the RAI-HRM and the employee innovative work behavior in the Jordanian commercial banks, with the employee trust in AI as a mediating mechanism. Based on the data from 249 bank employees that were analyzed with the PLS-SEM, the study found that the responsible AI practices in HR were strongly associated with the trust of the employees in AI ($\beta = 0.917$, $p < 0.001$), that the trust in AI was strongly associated with the innovative work behavior ($\beta = 0.900$, $p < 0.001$), and that the effect of the RAI-HRM on the innovative work behavior was transmitted through the trust ($\beta = 0.825$, $p < 0.001$). The model explained 84.1% of the variance in the trust in AI and 81.0% of the variance in the innovative work behavior. In other words, the employees are more likely to innovate with AI when they believe that AI is used in a transparent, fair, and secure manner and under a meaningful human control.

7.1 Theoretical Implications

The study provides three theoretical implications. First, it extends the social exchange theory to the context of the AI-enabled HRM, and it shows that the responsible governance of AI can be considered as a resource that the organization provides to the employees, and that the employees reciprocate this resource first through the trust and then through the innovative behavior. In this sense, the AI system is not only a technical tool, but it becomes also a part of the exchange relationship between the employee and the bank. Second, the study moves the research on the AI-enabled HRM beyond the adoption and the efficiency by conceptualizing and validating the RAI-HRM as a higher-order construct with six dimensions, and this responds to the call of Bujold et al. (2024) for the measurement of the responsible AI in the real organizational contexts, and especially regarding the accountability dimension which was insufficiently examined. Third, the study adds a critical point to the literature on the trust in AI, because the very high trust observed in this study, when it is read together with the inverted U-shaped argument of Lin et al. (2026), suggests that the social exchange based on the trust may have limits, and that the responsible governance should aim for a calibrated trust rather than a maximum trust. Moreover, the study provides an empirical evidence from the Jordanian banking sector, which is a context where the evidence on the responsible AI in HRM has been limited.

7.2 Practical Implications

For the bank managers and the HR professionals, the results indicate that the adoption of AI is not enough by itself to stimulate the innovation. The banks should explain to the employees how the AI-supported HR decisions are made, make the algorithmic outcomes understandable, protect the personal data of the employees, and establish clear procedures for the human review and the accountability. Moreover, because the excessive trust may encourage the automation bias, the banks should also train the employees to question the AI outputs and should keep the humans responsible for the sensitive decisions. In this regard, the degree of utilization of the digital skills by the employees should be assessed and developed (Hazaimah, 2025). For the policymakers and the banking regulators in Jordan, the findings can inform the guidelines on the responsible use of AI in the employment decisions, and these guidelines should protect the rights of the employees while they support the digital transformation. In addition, these guidelines can be aligned with the wider governmental strategies of the sustainable transformation, such as the taxation and the customs strategies that aim to enhance the environmental responsibility (Zobi et al., 2023; Al-Zaqeba, 2025).

7.3 Limitations and Future Research

The study has several limitations. First, the cross-sectional and single-source design does not allow the causal conclusions, and the common method variance cannot be fully excluded. Second, the innovative work behavior was self-reported, and this may overstate the actual behavior. Third, the structural model did not include a direct path from the RAI-HRM to the innovative work behavior, and therefore the study cannot distinguish between the partial and the full mediation (X. Zhao et al., 2010). Fourth, the very high reliability of the trust measure suggests some redundancy among its items, and the conceptual overlap between the trust and the dimensions of the RAI-HRM may have strengthened the observed relationships. Fifth, the demographic variables were not controlled in the structural model, and the possible non-response bias was not examined. Sixth, the sample was limited to the commercial banks in Jordan, and this limits the generalizability of the findings to other sectors and countries.

Accordingly, the future research could address these limitations by using the longitudinal or the multi-source designs, for example with the supervisor ratings of the innovative behavior, and by estimating the direct and the indirect effects of the RAI-HRM at the same time. Moreover, the researchers could refine the trust measure, examine the moderators such as the openness and the job complexity (Zhang et al., 2025), test the possible non-linear effect of the trust in AI that was suggested by Lin et al. (2026), and compare the model across different sectors and countries. For example, the model could be tested in the Islamic banks, where the interest-free financial instruments have specific characteristics and measurement problems (Al-Zaqeba & Basheti, 2024).

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