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Consequences of Implementing Artificial Intelligence in Human Resource Management of Iranian Government Organizations

Javad Rahdarpour[1], Hamid Okati[2*], Mostafa Ostovar[2]

[1] Assistant Professor, Department of Management, Islamic Azad University, Zabol branch, Zabol, Iran
[2] Master of Public Administration, Department of Management, Islamic Azad University, Zabol Branch, Zabol, Iran

*** Corresponding author email address**: hamidokati@yahoo.com

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ABSTRACT

The present study aimed to examine the consequences of implementing artificial intelligence in human resource management within Iranian government organizations. The research method, in terms of data type, is mixed-method (qualitative-quantitative); in terms of the research environment, it is library-based; and in terms of data collection method, nature, and research method, it is descriptive-correlational. In this research, interviews were used to identify the consequences. The statistical population in the qualitative section consisted of 5 experts from Iranian government organizations, and in the quantitative section, 335 employees from these organizations. The data collection tool in the qualitative section was interviews, while in the quantitative section, a researcher-made questionnaire based on a five-point Likert scale was used. For data analysis in the quantitative section, Cronbach's alpha tests, Average Variance Extracted (AVE), the AVE square root matrix, and confirmatory factor analysis using smartPLS software were employed. The results showed that the consequences of implementing artificial intelligence in human resource management in Iranian government organizations span five areas: recruitment, training, performance evaluation, compensation, and retention. Moreover, the results indicated that among the components, the recruitment component requires further strengthening.

Keywords: *Human resources, Human resource management, Artificial intelligence, Electronic recruitment*

1. Introduction

Today, the dynamics of markets are rapidly changing with the introduction of new technological solutions, particularly pervasive technologies (Dacko, 2017). Among these, practical technologies such as artificial intelligence (AI) are one of the greatest disruptors in the retail industry, quickly driving change (Krishen et al., 2021). According to Davenport et al. (2020), the widespread use of practical AI-embedded technology "may exist everywhere and in all corners, promising to change business models and consumer behavior." Applied AI technology can be explored in marketing strategies across a wide range of industries, particularly in the service sector, which includes entertainment and retail and comprises 80% of the U.S. economy (Fügener et al., 2022). AI is defined as systems that mimic human characteristics, including speech, learning, and problem-solving, which, by relying on the potential to augment and replace human tasks in industrial, intellectual, and social applications, support human cognitive functioning (Dwivedi et al., 2021).

The challenge for large companies is not only discovering and exploiting new technologies but also creating organizational change (Steiber et al., 2020). Digital transformation is currently one of the topics that researchers cannot overlook when formulating business strategies. Digital transformation is an industry-level phenomenon that changes how organizations compete within and between industries. Therefore, digital transformation "impacts products, business processes, sales channels, and supply chains," affecting large parts of companies and extending beyond their borders (Guimaraes, 2020).

The use of information technology (IT) by businesses as a strategic tool is not a new phenomenon (Dwivedi, 2009); however, the correlation between the use of AI technologies and organizational strategy is significantly more complex than with other technologies. In this context, deriving value from AI investments is more challenging than anticipated, due to the paradox of whether AI has the potential to transform company growth or simply imposes additional costs, which has been a subject of debate (Lichtenthaler, 2020).

Given the growing needs of human resources in addressing employee matters, dealing with large volumes of data and information, and other issues, AI has been proposed as a novel and useful solution for resolving problems and facilitating processes. The implementation of AI in human resource management (HRM) has provided comfort and satisfaction for employees, bringing about more favorable conditions for organizations. Therefore, it is essential that organizations, by strengthening research and applying AI according to their needs, take effective steps toward modernizing and optimizing this area. This will lead to long-term benefits and the growth and development of the organization (Chilunjika et al., 2022; Islami & Sopiah, 2022; Tewari & Pant, 2020).

In the digital age, where rapid development occurs, this transformation brings significant changes to the approach to HRM. Recruitment processes have become more efficient and precise with the adoption of online platforms and AI algorithms, enabling organizations to better identify and attract the best talent based on their needs (Albrecht et al., 2015). Digital performance management systems provide a broader view of individual and team achievements, while online training and collaboration tools facilitate the exchange of information and the development of skills (Bloom et al., 2014). One of the key features of AI is its ability to perform adaptive decision-making, where the system can respond to environmental dynamics or new information by changing its behavior without human intervention (Fügener et al., 2022). Implementing AI in HRM allows organizations to make recruitment processes more efficient through in-depth data analysis to identify the right talent and skills. AI can also facilitate performance management by providing precise analysis of individual and team productivity and performance. While AI contributes positively to the automation of routine tasks and increased efficiency, a careful approach to ethics and security in its implementation is required (Tewari & Pant, 2020). Therefore, integrating AI into HRM must be done with full consideration to ensure that the technology not only enhances organizational productivity but also adheres to ethical values and fairness in HR management. Based on the aforementioned discussions, this research examines the consequences of applying AI in HRM in Iranian government organizations.

2. Methods and Materials

Considering that the present research investigates the consequences of applying AI in HRM in Iranian government organizations, the research method, in terms of the occurrence of the phenomenon, is retrospective; in terms of the outcome, it is decision-oriented; in terms of the goal, it is applied; in terms of execution logic, it is both deductive and inductive; in terms of the research timeline, it is cross-sectional; in terms of data type, it is mixed-method (qualitative-quantitative); in terms of the research environment, it is library-based; in terms of data collection method and the nature and method of the research, it is descriptive-correlational; and in terms of the focus on the phenomenon, it is exploratory.

The statistical population in the qualitative section included experts from Iranian government organizations, and in the quantitative section, it included all employees of Iranian government organizations. The sample size in the qualitative section was determined by theoretical saturation (5 individuals), and in the quantitative section, based on Krejcie and Morgan's (1970) table, it was estimated at 335 individuals. For sample selection, purposeful sampling was used in the qualitative section, and stratified random sampling was employed in the quantitative section. The data collection tool in the qualitative section was interviews, while in the quantitative section, a researcher-made questionnaire based on a five-point Likert scale was used. Based on the interviews conducted, the components and indicators were modeled as shown in Table 1:

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Table 1

Identified Components and Indicators Through Interviews

Component	Indicator
Recruitment	Rapid screening and sorting of resumes and documents
	Accurate scheduling of interviews
	Reducing human error and preventing individuals' rights from being overlooked
	Precise matching of conditions with individuals' skills
Training	Accurate identification of the skills needed by the organization
	Identifying required training courses based on job requirements
	Aligning training with organizational goals
Performance Evaluation	Creating a data-driven performance evaluation system
	Evaluating employee performance based on an effective algorithm
	Reducing bias in performance evaluations
Compensation	Fair salary payments
	Personalizing rewards
	Evaluating the results and efficiency of rewards
	Smart reward systems based on individual performance
Retention	Predicting the likelihood of job turnover
	Predicting employee success in job rotations
	Identifying procrastination

The validity of the questionnaire, in terms of face and content validity, was confirmed by several experts. Convergent validity was confirmed through the calculation of Average Variance Extracted (AVE), and discriminant validity was confirmed through the calculation of the square root of AVE. The reliability of the questionnaire, calculated through Cronbach's alpha, was 0.894 for the entire questionnaire. For data analysis, Cronbach's alpha tests, AVE, AVE square root matrix, and confirmatory factor analysis using smartPLS software were used.

Based on the obtained data, the reliability of the dimensions is confirmed, as Cronbach's alpha and composite reliability coefficients are above 0.7. The results are as follows:

Table 2

Reliability of Research Variables

Variable	Cronbach's Alpha	Composite Reliability
Recruitment	0.799	0.714
Training	0.982	0.912
Performance Evaluation	0.857	0.928
Compensation	0.893	0.974
Retention	0.914	0.837

Additionally, AVE > 0.5 confirms convergent validity, as CR > 0.7, CR > AVE, and AVE > 0.5. Discriminant validity is also confirmed. The results are as follows:

Table 3

AVE and Correlation Between Research Variables

Variable	Recruitment	Training	Performance Evaluation	Compensation	Retention
Recruitment	0.695				
Training	0.425	0.594			
Performance Evaluation	0.427	0.357	0.724		
Compensation	0.316	0.257	0.212	0.625	
Retention	0.436	0.264	0.358	0.467	0.574

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3. Findings and Results

In this section, the demographic information and the descriptive statistics of the research variables, including measures of central tendency, dispersion, and distribution shape, are presented in Table 4. According to the descriptive findings, 19% of the respondents were women, and 81% were men. In terms of age, 23% of the respondents were under 30 years old, 41% were between 30 and 40 years old, 27% were between 40 and 50 years old, and 9% were over 50 years old. Regarding work experience, 17% of the respondents had less than 10 years of experience, 67% had between 10 and 20 years, and 16% had more than 20 years.

Table 4

Descriptive Statistics of Research Variables

Component	Mean	Standard Deviation	Skewness	Kurtosis
Recruitment	3.014	0.84	0.25	-0.41
Training	3.503	0.80	0.00	-0.08
Performance Evaluation	3.345	0.71	0.01	0.47
Compensation	3.157	0.75	0.14	0.22
Retention	3.455	0.83	-0.22	0.17

The mean and standard deviation for all components are presented. Based on the results, all data have a mean above 3.

To assess the model fit, confirmatory factor analysis was conducted using smartPLS software.

Figure 1

Path Coefficients and Factor Loadings

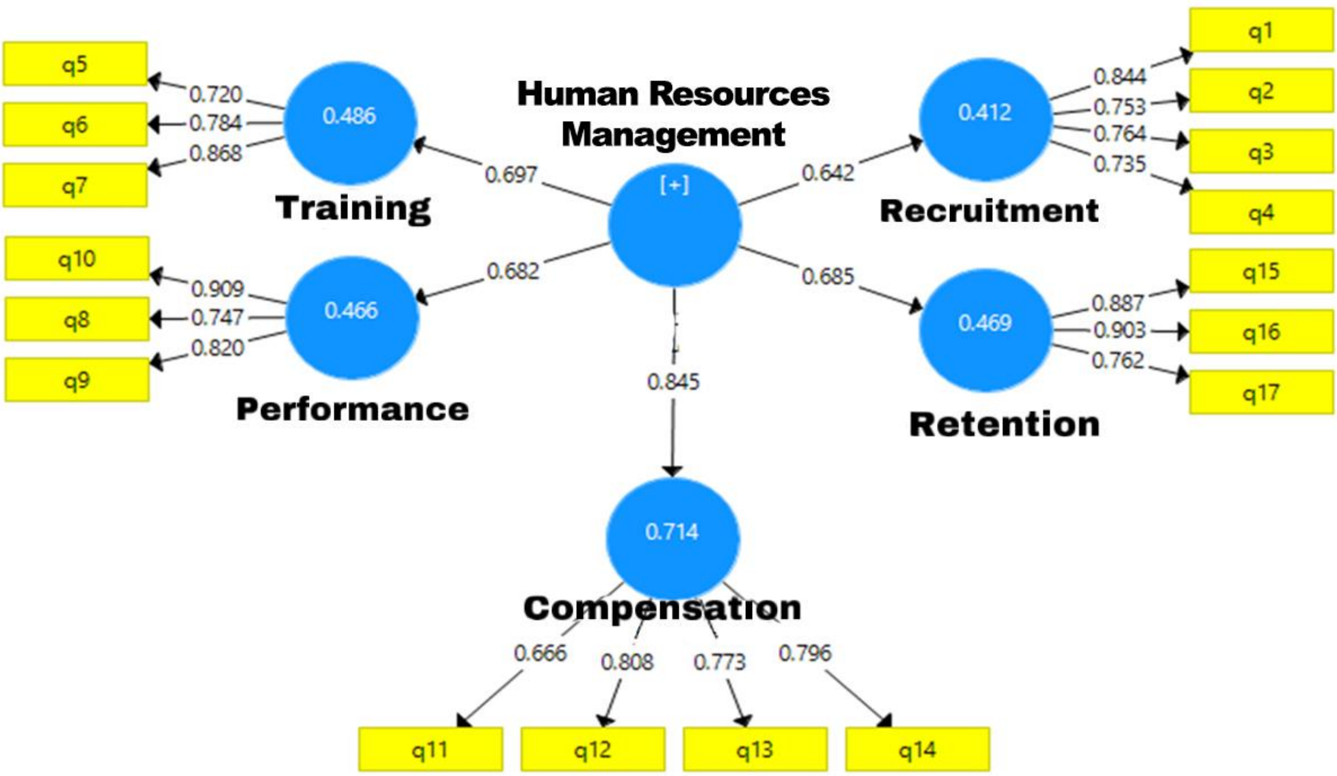

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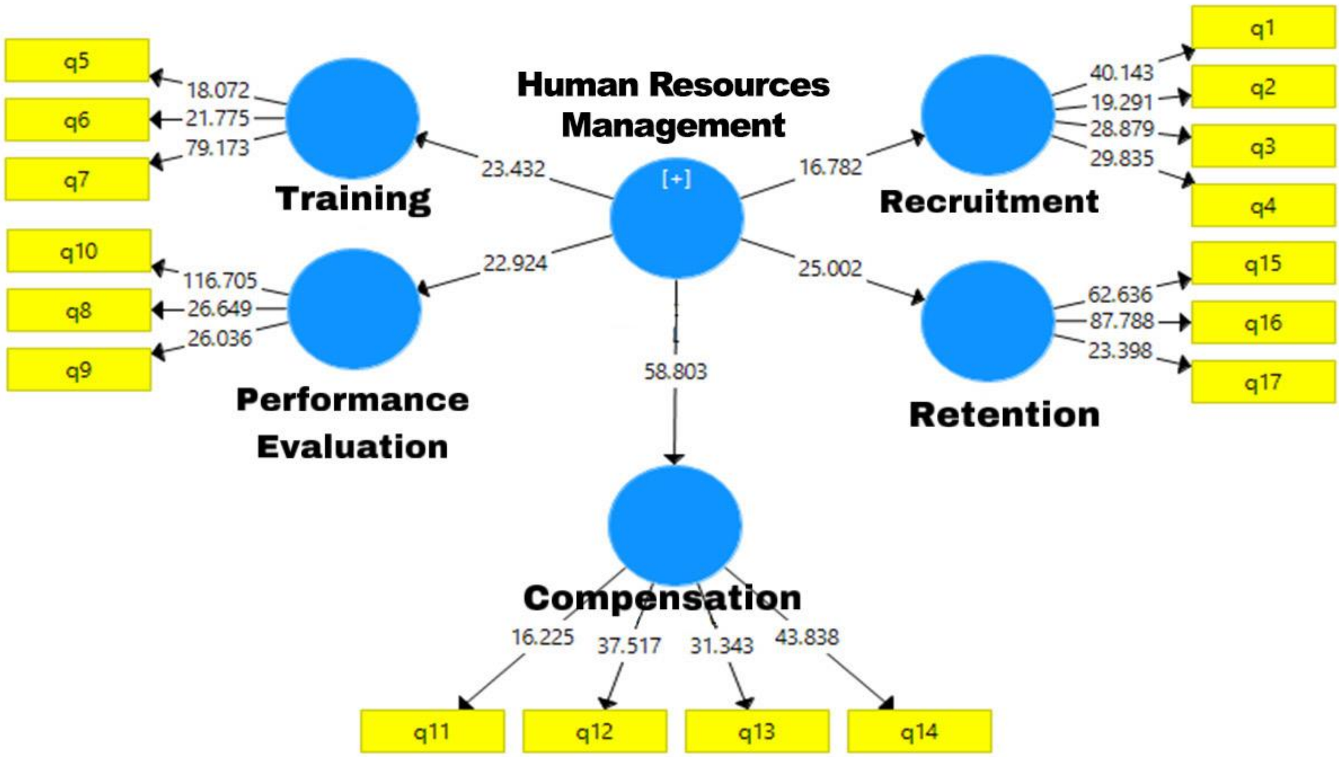
Figure 2

Significance (t-statistic) of the Model



The numbers on the paths represent the path coefficients. To test the significance of the path coefficients, the t-statistic was calculated using the bootstrap method. If the t-statistic is greater than 2.58, the path coefficient is significant at the 0.05 level.

The R^2 coefficient pertains to the endogenous (dependent) latent variables and shows the effect of an independent variable on a dependent variable. The thresholds for R^2 values are 0.19 for weak, 0.33 for moderate, and 0.67 for strong effects. The R^2 values for the constructs of the main model were calculated as 0.412, 0.469, 0.714, 0.466, and 0.486.

The interpretation criteria for Q^2 are 0.02 for weak, 0.15 for moderate, and 0.35 for strong predictive power. A positive Q^2 value is desirable. The Q^2 values for the research variables were calculated as 0.293, 0.232, 0.218, 0.298, and 0.241, which are positive and at a desirable level. Based on this, it can be concluded that the model has good predictive power for the variables.

The GOF (Goodness of Fit) index, introduced by Tenenhaus et al. (2005), is a general fit measure. Structural equation modeling experts using the PLS method regard a GOF value of less than 0.10 as small, between 0.10 and 0.25 as moderate, and above 0.36 as large. The GOF for the sample model in this study was 0.665, which falls within the large range. Based on these findings, it can be concluded that the tested model has an appropriate fit. Additionally, given that the factor loadings for all observed variables in the model are greater than 0.5 and the significance values are higher than 2.58, the present construct has good validity.

Since the scale used is a five-point Likert scale, we considered a numerical value of 3 for comparison with the t-statistic.

The results of the one-sample t-test are presented in Table 5.

Table 5

One-Sample t-Test to Examine the Current Situation (Test Value = 3)

Variable	t-Value	Sig.	Mean	Lower Bound (CI: 95%)	Upper Bound (CI: 95%)
Recruitment	51.431	0.000	3.014	2.898	3.129
Training	70.722	0.000	3.503	3.405	3.601
Performance Evaluation	60.466	0.000	3.345	3.235	3.454
Compensation	46.291	0.000	3.157	3.022	3.292
Retention	68.966	0.000	3.455	3.356	3.554

As shown in the table, the significance level for all components is less than 0.05, and therefore, the null hypothesis is rejected with 95% confidence, confirming the research hypothesis. In other words, the status of these components is favorable (given that the mean differences are positive). For the recruitment component, since the mean is only slightly above 3, it can be said that it needs strengthening, and measures should be taken in this area.

4. Discussion and Conclusion

The findings of this study shed light on the consequences of applying Artificial Intelligence (AI) in human resource management (HRM) within Iranian government organizations, focusing on five key areas: recruitment, training, performance evaluation, compensation, and retention. The data analysis revealed that all components scored above 3, with the highest scores related to training and retention, while recruitment scored the lowest. These findings indicate that AI can significantly enhance the HR processes of Iranian government organizations, although recruitment practices may require further improvements.

The results show that recruitment, while benefitting from AI, still needs considerable attention and improvement. The mean score for this component was the lowest (3.014), suggesting that the current AI-driven recruitment systems are not fully optimized. This finding aligns with earlier studies that highlighted the complexities of integrating AI into recruitment (Albrecht et al., 2015). AI's ability to quickly sift through resumes and schedule interviews is well documented, but its potential for reducing human error and bias has not yet been fully realized (Dwivedi et al., 2021). Krishen et al. (2021) argue that while AI can reduce recruitment times and enhance the accuracy of matching candidates to job roles, organizations must invest in refining AI algorithms to avoid perpetuating biases that may be embedded in historical data (Krishen et al., 2021). Therefore, recruitment processes should not just rely on AI but also be complemented with human oversight to mitigate risks associated with biased decision-making (Tewari & Pant, 2020).

AI has shown the greatest impact on the training component, with a mean score of 3.503. This result suggests that AI is effectively improving the accuracy of identifying organizational skill gaps and aligning training programs with organizational goals. This finding is consistent with the work of Bloom et al. (2014), who demonstrated that AI-driven platforms for online training can facilitate skill development by providing personalized learning experiences (Bloom et al., 2014). AI's ability to continuously analyze employee performance and suggest relevant training based on real-time data is also noted by Albrecht et al. (2015). Furthermore, the use of AI to tailor training programs to individual employee needs can help organizations optimize learning outcomes and ensure that the workforce remains aligned with organizational goals (Albrecht et al., 2015; Dwivedi et al., 2021).

In the performance evaluation component, the results showed a mean score of 3.345. AI appears to be helping organizations create data-driven performance evaluation systems that are less susceptible to human bias. This result is in line with the findings of Tewari and Pant (2020), who found that AI's capacity to process large volumes of employee data enhances the objectivity of performance evaluations (Tewari & Pant, 2020). By relying on performance data collected over time, AI can provide deeper insights into employee productivity and performance trends (Bloom et al., 2014). However, concerns about over-reliance on AI systems in performance evaluation persist, particularly regarding the risk of employees feeling alienated if evaluations are entirely automated (Fügener et al., 2022). Therefore, organizations should strike a balance by using AI to support rather than replace human judgment in performance reviews.

The compensation component had a mean score of 3.157, indicating that while AI contributes to the fair distribution of rewards and compensation, there is room for improvement. AI systems are being used to assess the effectiveness of compensation packages and personalize rewards based on performance metrics (Albrecht et al., 2015). This ability to tailor compensation and rewards to individual employees is crucial for maintaining employee satisfaction and motivation. However, as Krishen et al. (2021) have noted, AI-driven compensation systems must be continuously monitored to ensure fairness, particularly regarding the potential for bias in the algorithm's decision-making processes (Krishen et al., 2021). A transparent AI system is essential to build trust among employees and ensure that compensation decisions are viewed as just.

AI also showed a significant impact on employee retention, with a mean score of 3.455. AI's ability to predict employee turnover by analyzing patterns in employee behavior, such as engagement and performance metrics, aligns with the literature (Dwivedi et al., 2021). By identifying employees who may be at risk of leaving, organizations can intervene early and address issues that may lead to turnover (Tewari & Pant, 2020). This proactive approach to retention helps organizations reduce turnover costs and retain top talent. The positive results in this area are further supported by Fügener et al. (2022), who highlight the importance of AI in predicting employee satisfaction and mitigating retention risks (Fügener et al., 2022).

One limitation of this study is the sample size and the generalizability of the results. While 335 employees from various Iranian government organizations participated in the quantitative phase, the findings may not be fully representative of all government organizations or transferable to private sector organizations. Additionally, cultural and organizational factors unique to Iran could influence the adoption and effectiveness of AI in HRM, which may not apply in different geopolitical contexts. Another limitation is the cross-sectional nature of the study. As AI technologies are continuously evolving, a longitudinal study could provide more insight into how the application of AI in HRM impacts organizations over time.

The reliance on self-reported data in the quantitative phase also presents potential biases. Respondents may have over- or under-reported the effectiveness of AI tools in their organizations due to personal beliefs or experiences. Finally, the study did not delve deeply into the ethical implications of AI in HRM, a critical area that warrants further exploration given the potential for bias in AI algorithms and the impact on employee fairness and trust.

Future research should expand the scope of this study to include a larger and more diverse sample, encompassing both public and private sector organizations across various industries. Comparative studies between sectors could help to identify sector-specific challenges and benefits of AI implementation in HRM. Additionally, future research should adopt a longitudinal approach to explore the long-term effects of AI on organizational outcomes such as employee satisfaction, performance, and turnover rates. This would provide valuable insights into how AI tools evolve and adapt to changing organizational needs over time.

Another area for future research is the ethical considerations of AI in HRM. Studies should focus on understanding how organizations can mitigate algorithmic biases and ensure fairness in AI-driven decisions. Exploring the role of human oversight in AI systems, particularly in sensitive areas like recruitment and performance evaluation, is crucial to ensuring that AI enhances rather than undermines fairness and equity in HRM. Finally, research should investigate employee perceptions of AI in HRM, particularly regarding trust, transparency, and the potential loss of human interaction in critical HR functions.

For organizations seeking to implement AI in their HRM processes, several practical recommendations emerge from this study. First, while AI can streamline recruitment processes, organizations must invest in refining AI algorithms to ensure that they do not perpetuate biases present in historical data. Human oversight should be maintained to ensure that recruitment decisions are fair and equitable. Training programs should also be tailored using AI to address the specific skill gaps and career development needs of employees, ensuring alignment with organizational goals.

In terms of performance evaluation, organizations should use AI as a tool to support rather than replace human judgment. AI systems can provide valuable insights into employee performance, but human managers should remain involved to interpret the data and make final decisions. This hybrid approach can help avoid the alienation of employees and ensure that performance reviews are comprehensive and fair.

Finally, organizations should leverage AI to predict employee turnover and implement proactive retention strategies. AI tools can help identify employees who may be at risk of leaving and suggest interventions to improve their engagement and satisfaction. However, it is crucial that AI-driven retention strategies are implemented

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transparently, with clear communication to employees about how AI is being used and how decisions are made.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

J. R., H. O., and M. O. contributed collaboratively to the research on the consequences of implementing artificial intelligence in human resource management within Iranian government organizations. J. R. conceptualized the study and led the qualitative and quantitative data collection efforts, coordinating the interviews with experts and overseeing the administration of the questionnaires to government employees. H. O. played a key role in the qualitative phase, conducting the expert interviews and analyzing the interview data to identify the key themes and consequences of AI implementation. His work was crucial in shaping the research framework and identifying the five main areas of impact: recruitment, training, performance evaluation, compensation, and retention. M. O. handled the quantitative data analysis, applying statistical tests and confirmatory factor analysis using smartPLS software. He was responsible for ensuring the reliability and validity of the quantitative findings and for interpreting the statistical results, particularly the need for strengthening the recruitment component. Together, the authors collaborated on the design, execution, and writing of the study.

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