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The Mechanism of Trust in Technology in the Relationship Between the Artificial Emotional Intelligence of Human Resource Chatbots and Employees' Satisfaction with HR Services (A Case Study of Employees at the Science and Research Branch, Tehran)

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Abstract

The present study aimed to investigate the mechanism of trust in technology in the relationship between the artificial emotional intelligence of human resource (HR) chatbots and employees' satisfaction with HR services at the Science and Research Branch, Tehran. In terms of purpose, this research was applied, and in terms of approach, it employed a quantitative methodology with a descriptive–survey correlational design. The statistical population consisted of all employees of the Science and Research Branch, Tehran (N = 248). Based on Cochran's formula, a sample of 150 participants was selected using convenience sampling. Data were collected through a researcher-developed questionnaire using a five-point Likert scale. For data analysis, descriptive statistics were first employed to describe the characteristics of the sample and the study variables, and the normality of the data was assessed using the Kolmogorov–Smirnov test. Subsequently, to test the relationships among variables and validate the research model, structural equation modeling (SEM) using the partial least squares (PLS) approach was conducted in SmartPLS software. The significance of the path coefficients was evaluated through bootstrapping and the t-statistic criterion, and model fit indices appropriate for PLS-SEM were reported. Instrument validity was assessed and confirmed through convergent validity, discriminant validity, and examination of factor loadings, while reliability was evaluated and confirmed using Cronbach's alpha, composite reliability, and rho coefficient. The findings indicated that the artificial emotional intelligence of HR chatbots is associated with increased trust in technology and enhanced employee satisfaction with HR services. Furthermore, trust in technology played a significant mediating role in explaining this relationship. Therefore, strengthening emotional dimensions in the design and implementation of HR chatbots can improve employees' experiences and satisfaction with HR services through the enhancement of trust.

Keywords: Trust in Technology, Artificial Emotional Intelligence, Human Resource Chatbots, Employee Satisfaction, Science and Research Branch, Tehran.

1. Introduction

The rapid digitalization of organizational processes has repositioned human resource management (HRM) from an administratively oriented function toward a technology-mediated strategic system that supports decision-making, employee experience, service delivery, and organizational agility. In this transformation, artificial intelligence (AI) has become one of the most influential technological forces reshaping how HR departments communicate with employees, process requests, analyze workforce data, and provide personalized support. Earlier debates on electronic HRM emphasized that technology should not be treated merely as a technical infrastructure but as a managerial and organizational phenomenon that changes HR roles, service relationships, and the nature of employee–organization interaction (Bondarouk & Brewster, 2016). This perspective has become more relevant with the emergence of digital HRM, which extends beyond automation and integrates digital technologies into HR processes, structures, and value creation mechanisms (Strohmeier, 2020). Accordingly, contemporary HRM increasingly depends on intelligent systems capable of supporting recruitment, training, performance management, employee services, and strategic workforce planning.

AI-based HRM has attracted growing scholarly attention because it promises efficiency, scalability, predictive insight, and personalization in people management. AI applications in HR can improve the quality of decision-making, reduce repetitive administrative workloads, and assist managers in handling complex workforce-related information; however, such technologies also raise concerns about fairness, transparency, accountability, privacy, and employee acceptance (Tambe et al., 2019). Systematic evidence indicates that AI, robotics, and advanced technologies are transforming multiple HRM domains, yet their successful implementation depends not only on technical performance but also on organizational readiness, employee perceptions, ethical governance, and the alignment of technology with human-centered HR objectives (Vrontis et al., 2022). In this regard, HR technology must be understood as a socio-technical phenomenon in which algorithmic capability and human trust jointly determine whether digital HR initiatives generate meaningful organizational value.

One of the most visible manifestations of AI in HR service delivery is the chatbot. Chatbots are conversational agents designed to interact with users through natural language and provide automated responses, guidance, or task support. The recent development of generative conversational AI has further intensified interest in chatbot systems by expanding their ability to generate context-sensitive responses, support knowledge work, and participate in organizational communication processes (Dwivedi et al., 2023). In HRM, chatbots can be used to answer frequently asked questions, guide employees through administrative procedures, support onboarding, facilitate training access, provide policy-related information, and offer immediate responses to service requests. This makes HR chatbots particularly relevant in large organizations and universities, where employees often require timely, accurate, and accessible HR services. Nevertheless, the effectiveness of such systems depends on more than speed and availability; employees must perceive chatbot interactions as reliable, understandable, supportive, and emotionally appropriate.

The literature on chatbot research shows that future studies should move beyond technical performance and examine the psychological, social, ethical, and experiential dimensions of human–chatbot interaction (Følstad et al., 2021). In organizational service contexts, employees do not interact with chatbots only as information retrieval tools; they may also interpret their tone, responsiveness, empathy, and sensitivity to user needs. Evidence from AI-based customer service indicates that chatbot design features can influence user compliance and behavioral responses, suggesting that conversational agents can shape user attitudes and actions through interaction quality (Adam et al., 2021). For HRM, this insight is highly significant because HR services are often connected to personal concerns, workplace expectations, perceived support, and organizational justice. Therefore, HR chatbots that fail to recognize employees' emotional states or provide supportive responses may be perceived as mechanical, impersonal, or even alienating, whereas emotionally responsive systems may strengthen employees' sense of service quality and organizational care.

This issue has directed attention to artificial emotional intelligence, which refers to the capacity of AI systems to perceive, interpret, respond to, and regulate emotional cues during interaction. In the context of HR chatbots, artificial emotional intelligence may include the ability to identify emotional tone in employee messages, respond empathetically, reduce tension during service encounters, and adapt communication style to the user's affective state. Such capabilities are particularly important because HR interactions often involve sensitive topics such as job concerns, administrative uncertainty, benefits, conflict, workload, training needs, and career development. When employees perceive that an HR chatbot understands their emotional condition and responds in an appropriate and supportive manner, the interaction may become more human-centered and less transactional. This can contribute to satisfaction with HR services by improving the perceived quality, usefulness, and responsiveness of digital HR service delivery.

However, the integration of AI into HRM also generates critical concerns related to dehumanization and negative employee reactions. Recent research has warned that AI in HRM may be perceived as a driver of organizational dehumanization when employees feel that algorithmic systems replace human judgment, reduce interpersonal care, or treat workers as data objects rather than organizational members (Shin et al., 2025). This concern is especially relevant for HR chatbots because they directly mediate the relationship between employees and HR departments. If chatbot interactions are emotionally insensitive or opaque, employees may experience dissatisfaction or distrust. Conversely, artificial emotional intelligence may mitigate dehumanization by making chatbot-mediated HR services feel more attentive, respectful, and relational. Therefore, the emotional quality of chatbot interaction should be considered a central design and implementation factor in AI-enabled HRM.

Trust in technology is a core mechanism through which employees evaluate and accept AI systems. Human trust in AI has been identified as a multidimensional construct shaped by perceived competence, reliability, transparency, predictability, and ethical acceptability (Glikson & Woolley, 2020). In HRM, trust becomes particularly important because AI systems may influence employee data, service access, administrative outcomes, and perceptions of organizational fairness. Employees may hesitate to use HR chatbots if they doubt the accuracy of responses, fear misuse of personal information, or perceive the system as unable to understand their concerns. Thus, even when AI tools are technically advanced, their organizational effectiveness may remain limited if users do not trust them. Trust in technology can therefore be regarded as a psychological bridge between AI capabilities and employee satisfaction with HR services.

Explainability and causability are also critical for trust in AI. When users understand why an AI system provides a particular response or recommendation, they are more likely to perceive it as trustworthy and acceptable (Shin, 2021). In HR chatbot services, explainability may involve clear communication, transparent limitations, consistent responses, and understandable guidance. Emotional intelligence can complement explainability by making these interactions not only cognitively understandable but also affectively acceptable. For example, a chatbot that explains HR procedures in a clear but cold manner may be useful, but a chatbot that combines clarity with empathy may generate stronger trust and satisfaction. Therefore, artificial emotional intelligence may contribute to technology trust both directly, by improving the emotional tone of interaction, and indirectly, by enhancing perceptions of responsiveness, predictability, and service appropriateness.

The growing strategic role of AI in HRM has also been emphasized in recent studies that highlight its capacity to transform talent acquisition, employee development, training, decision-making, and organizational adaptability. AI is increasingly presented as a driver of strategic transformation in talent acquisition and management, enabling organizations to process large volumes of information and create more efficient HR workflows (Tak, 2025). Similarly, AI has been described as a key factor in reinventing HRM by supporting automation, analytics, and more intelligent workforce management practices (Subrahmanyam, 2025). Recent discussions also show that AI can transform HRM by improving the integration of digital systems into employee-related functions and enabling more adaptive forms of organizational management (Sharifi et al., 2025). These contributions indicate that AI adoption in HRM should not be limited to operational automation; rather, it should be examined as a strategic shift that reshapes the employee experience and the perceived quality of HR services.

At the same time, AI implementation in HRM involves substantial challenges. Studies on AI applications in HRM systems show that although AI can enhance HR efficiency and decision support, organizations must address implementation barriers such as data quality, employee resistance, ethical concerns, and the need for managerial competence (Moghadam et al., 2025). AI-based HRM training has also been identified as an important area because employees and HR professionals need sufficient knowledge to use intelligent systems effectively and responsibly (Orhan & Kurnaz, 2025). These concerns suggest that the success of HR chatbots depends not only on the availability of the technology but also on how employees experience, understand, and trust it. In this respect, trust in technology may function as an essential mediating variable that explains why emotionally intelligent chatbot systems lead to more favorable employee responses.

AI-enabled HRM is also increasingly discussed in relation to resilience, agility, and sustainability. Research in the hospitality industry has shown that HRM and AI can contribute to agile and resilient supply chains, indicating that AI-supported people management may strengthen organizational responsiveness in dynamic environments (Sadeghi et al., 2025). In healthcare, the integration of AI and Industry 5.0 has been linked to the transformation of HRM through more adaptive, human-centered, and technology-supported practices (Temjanovski et al., 2025). Similarly, sustainable integration of AI in HR digitalization within the context of Industry 4.0 emphasizes that AI should be embedded in organizational systems in a way that supports long-term value creation, digital maturity, and responsible HR transformation (Thomas et al., 2026). These studies collectively highlight that AI in HRM should be assessed not only through efficiency outcomes but also through its contribution to sustainable, trusted, and employee-centered service systems.

Employee satisfaction with HR services is a crucial outcome because HR services shape employees' daily experience of the organization. Satisfaction with HR services may depend on the perceived quality, speed, accessibility, usefulness, and emotional appropriateness of HR interactions. In traditional HR service encounters, employees often rely on human HR staff for guidance, reassurance, and problem-solving. When chatbots replace or supplement these encounters, satisfaction may depend on whether employees perceive the chatbot as capable of providing accurate information while also maintaining a supportive interaction climate. Therefore, the emotional intelligence of HR chatbots can be expected to influence satisfaction by improving both functional and relational aspects of service delivery. Emotion perception and recognition may help the chatbot identify employee concerns; empathic responses may enhance perceived support; and emotion regulation in interaction may reduce frustration and improve service experience.

Despite the growing literature on AI in HRM, several research gaps remain. First, much of the existing literature has focused on strategic AI applications, HR analytics, recruitment, automation, and decision-making, while fewer studies have examined the emotional and relational qualities of HR chatbot interactions. Second, although trust in AI has been widely recognized as essential, its mediating role in the relationship between artificial emotional intelligence and employee satisfaction with HR services requires further empirical examination. Third, universities and higher education institutions represent complex service organizations in which employees interact with administrative systems regularly, but the dynamics of AI-based HR service satisfaction in such settings remain underexplored. Fourth, the literature suggests both opportunities and risks in AI-enabled HRM, including efficiency and personalization on one hand and dehumanization and distrust on the other; therefore, empirical models are needed to clarify the conditions under which HR chatbots generate positive employee outcomes.

Accordingly, examining trust in technology as a mechanism linking artificial emotional intelligence and satisfaction with HR services can contribute to both theory and practice. Theoretically, it extends AI-enabled HRM research by integrating emotional intelligence, trust, and employee satisfaction in a single explanatory model. Practically, it can help HR managers and technology designers understand that successful chatbot implementation requires more than technical automation; it requires emotionally intelligent, transparent, reliable, and trust-building interaction design. For universities and similar knowledge-based organizations, such insights can guide the development of HR chatbots that improve employee experience while preserving the human-centered values of HRM. The aim of this study was to examine the mechanism of trust in technology in the relationship between the artificial emotional intelligence of HR chatbots and employees' satisfaction with HR services among employees of the Science and Research Branch, Tehran.

2. Methods and Materials

In terms of purpose, this study was applied, and in terms of approach, it was conducted as a quantitative descriptive–survey study of the correlational type. The data collection instrument was a researcher-developed questionnaire based on a five-point Likert scale ranging from 1 to 5. The statistical population of the study included all employees of the Science and Research Branch, Tehran, totaling 248 individuals. From this population, 150 individuals were selected as the statistical sample using Cochran's formula and the convenience sampling method. To analyze the data, descriptive statistics were first used to describe the characteristics of the sample and the variables, and the normality of the data was examined using the Kolmogorov–Smirnov test. Subsequently, to test the relationships and validate the model, structural equation modeling using the partial least squares approach (PLS-SEM) was applied in SmartPLS software, and the significance of the coefficients was assessed through bootstrapping and the t-statistic criterion. In addition, model fit indices appropriate for PLS, including SRMR, NFI, RMS_theta, and GOF, were reported to evaluate model adequacy. The validity of the instrument was assessed through convergent validity, average variance extracted (AVE), discriminant validity based on the Fornell–Larcker criterion, and examination of factor loadings in the measurement model, and it was confirmed. Reliability was also evaluated using Cronbach's alpha and composite reliability (CR), and it was confirmed. All details related to validity, reliability, and analytical results are presented comprehensively in the findings section. In conducting the study, respondents' participation was voluntary, data confidentiality was observed, and the results were reported only in aggregate form.

3. Findings and Results

This section of the study addresses the descriptive analysis of the data and the testing of the research hypotheses.

The analysis of the demographic variables of employees at the Science and Research Branch, Tehran (n = 150), showed that 109 employees (72.7%) were male and 41 employees (27.3%) were female. In terms of educational level, 33 employees (22%) held an associate degree, 88 employees (58.7%) held a bachelor's degree, and 29 employees (19.3%) had postgraduate education. In terms of work experience, 50 employees (33.3%) had 10 years or less of experience, 49 employees (32.7%) had 11 to 20 years of experience, and 51 employees (34%) had more than 20 years of experience.

The conceptual model of the study includes three main constructs, 11 subconstructs, and 32 items measured on a five-point Likert scale.

The descriptive statistics related to the responses of employees at the Science and Research Branch, Tehran, to each of the research constructs are presented in Table 1.

Table 1. Descriptive Statistics of the Research Constructs

Research Constructs	N	Mean	Median	Mode	Standard Deviation	Range	Minimum	Maximum
Efficiency component	150	1.848	1.666	1.67	0.757	4	1	5
Reliability component	150	1.946	2.000	2.00	0.781	4	1	5
Integrity and transparency component	150	2.280	2.000	1.33	0.986	4	1	5
Security and privacy component	150	2.231	2.000	2.00	0.675	3.67	1	4.67
Predictability component	150	2.393	2.333	2.00	0.694	3.67	1	4.67
Quality component	150	2.302	2.000	1.67	0.905	4	1	5
Speed component	150	2.235	2.000	1.67	0.737	4	1	5
Ease and usefulness of HR services component	150	2.580	2.333	2.33	0.661	3.33	1.33	4.67
Emotion perception and recognition component	150	3.275	3.333	4.00	1.040	4	1	5
Empathy and empathic response component	150	2.688	2.666	2.67	0.724	3.67	1.33	5
Emotion regulation in interaction component	150	2.277	2.000	2.00	0.877	3.67	1	4.67
Trust in technology variable	150	2.140	2.066	1.80	0.547	3.10	1.13	4.23
Employee satisfaction with HR services variable	150	2.375	2.222	2.11	0.615	3.11	1.44	4.56
Artificial emotional intelligence of the chatbot variable	150	2.747	2.777	2.67	0.652	3.33	1.33	4.67

Based on the data presented in Table 1, 150 valid data points were collected for the research variables. The median and mode also indicate that most participants selected options 2 and 3, namely "low" and "moderate," on the Likert scale in the questionnaire. The dispersion is high in terms of the range index and covers values between 1 and 5. Accordingly, the range of variation for most research variables is 4.

To select the appropriate statistical method, the normality of the data was first examined. For this purpose, the Kolmogorov–Smirnov test was used at the 5% error level. The statistical hypotheses were formulated as follows:

H_0: $Z \geq 0.05$; the data distribution is normal.

H_1: $Z < 0.05$; the data distribution is not normal.

If the significance value is greater than or equal to the error level (0.05), the data distribution is considered normal. The results of the normality assessment are presented in Table 2.

Table 2. Data Normality Test

Research Constructs	N	Skewness	Kurtosis	KS Statistic	Significance Value
Efficiency component	150	1.532	3.368	0.175	0.077
Reliability component	150	1.161	2.432	0.233	0.064
Integrity and transparency component	150	0.880	-0.026	0.160	0.060
Security and privacy component	150	1.279	2.593	0.173	0.100

Predictability component	150	0.855	1.472	0.188	0.145
Quality component	150	1.186	0.573	0.284	0.053
Speed component	150	1.162	2.118	0.152	0.057
Ease and usefulness of HR services component	150	0.816	0.793	0.165	0.055
Emotion perception and recognition component	150	-0.363	-0.885	0.077	0.685
Empathy and empathic response component	150	0.518	0.196	0.126	0.063
Emotion regulation in interaction component	150	0.899	0.355	0.178	0.135
Trust in technology variable	150	1.282	2.294	0.105	0.076
Employee satisfaction with HR services variable	150	1.554	2.704	0.190	0.105
Artificial emotional intelligence of the chatbot variable	150	0.326	0.146	0.052	0.783

Based on the results of Table 2, in all cases, the significance value is greater than the 5% error level. Therefore, the distribution of the data is normal, and both parametric and nonparametric methods can be used. In terms of skewness and kurtosis, the data are not far from normality, which increases the predictive power of the model.

The partial least squares technique was used to validate the model. The results obtained from running the model in the standardized estimation mode indicate the direction and strength of the relationship among the variables. The SmartPLS output for standardized estimation is presented in Figure 1.

To examine the significance of the relationships among the model variables, the bootstrapping method was used, which produces the t-statistic. At the 5% error level, if the bootstrapping statistic is greater than 1.96, the observed correlations are significant. The t-statistic and bootstrapping value used to assess the significance of the relationships are presented in Figure 2.

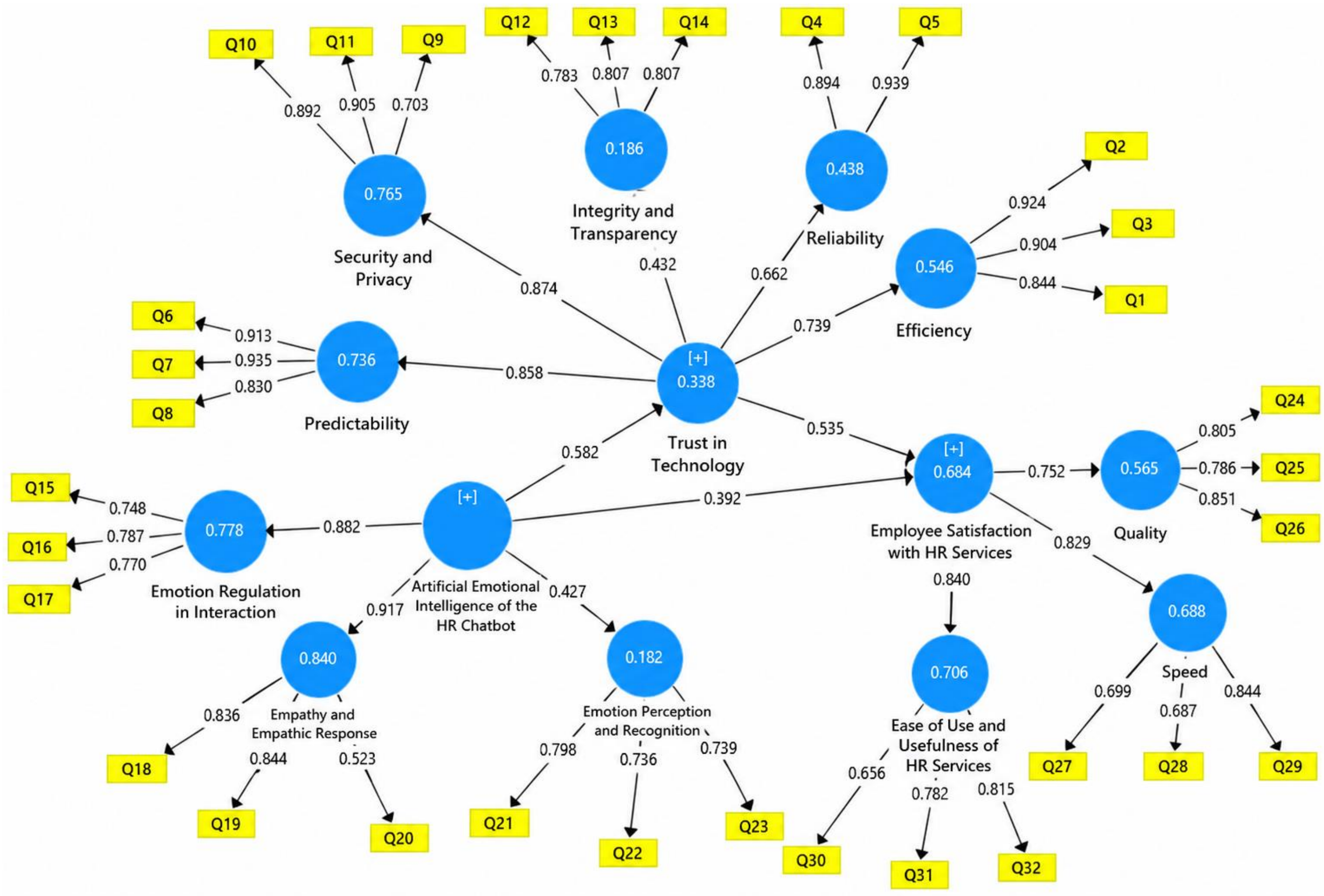

Figure 1. Model validation output using the partial least squares method.

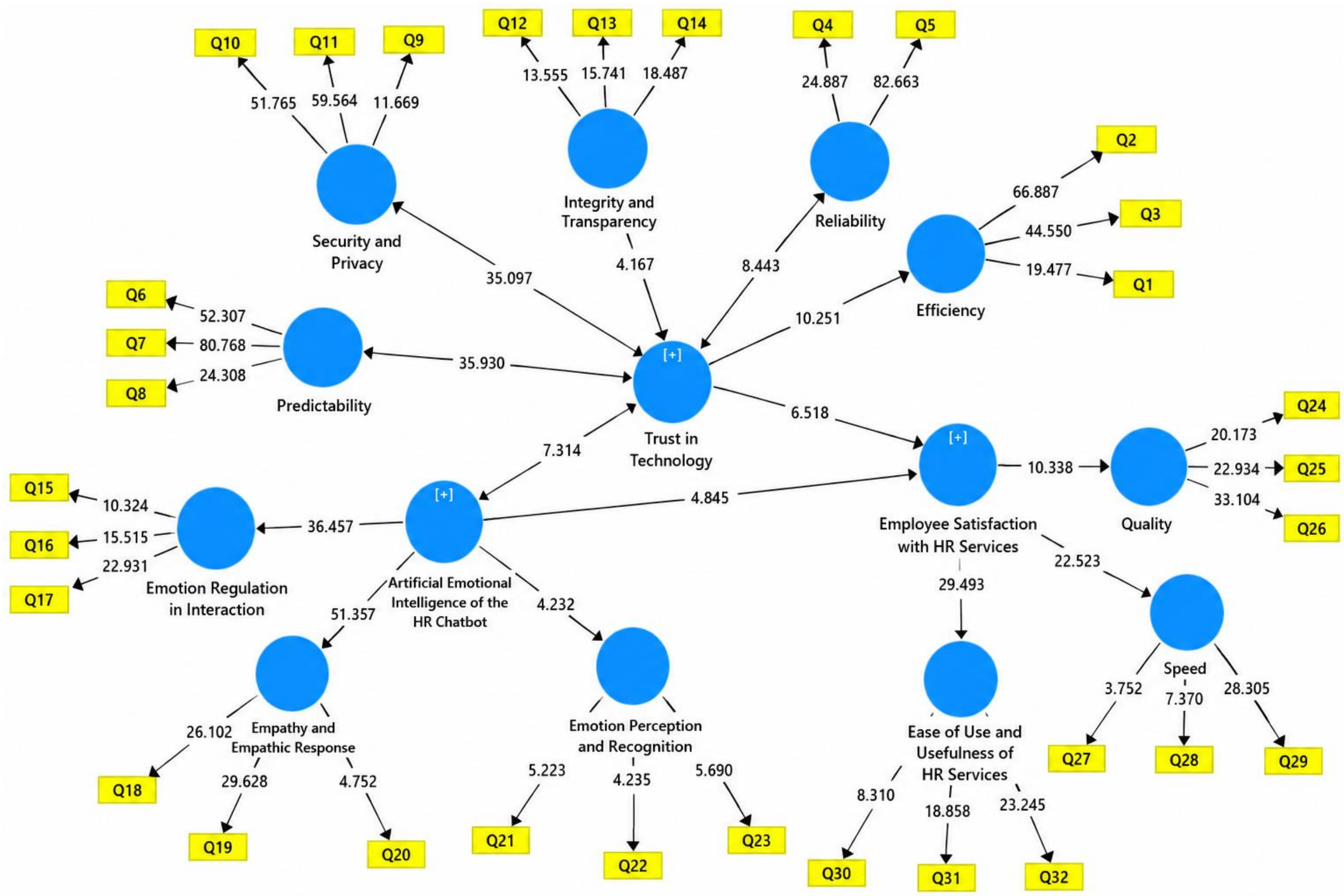

Figure 2. Significance of the relationships among variables using the partial least squares method (bootstrapping).

The relationships among the main research constructs were examined in the structural section. A summary of the results of the structural section of the model, namely the relationships among the model constructs, is presented in Table 3.

Table 3. Summary of the Results of the Structural Section of the Model: Relationships Among Model Constructs

Relationship	Path Coefficient	t-Statistic	Significance	Result
Artificial emotional intelligence of the chatbot → employee satisfaction with HR services	0.392	4.845	0.000	Confirmed
Artificial emotional intelligence of the chatbot → trust in technology	0.582	7.314	0.000	Confirmed
Artificial emotional intelligence of the chatbot → trust in technology → employee satisfaction with HR services	0.311	4.675	0.000	Confirmed

Based on the path coefficient and the t-statistic value obtained through bootstrapping, the relationships among the constructs can be interpreted as follows:

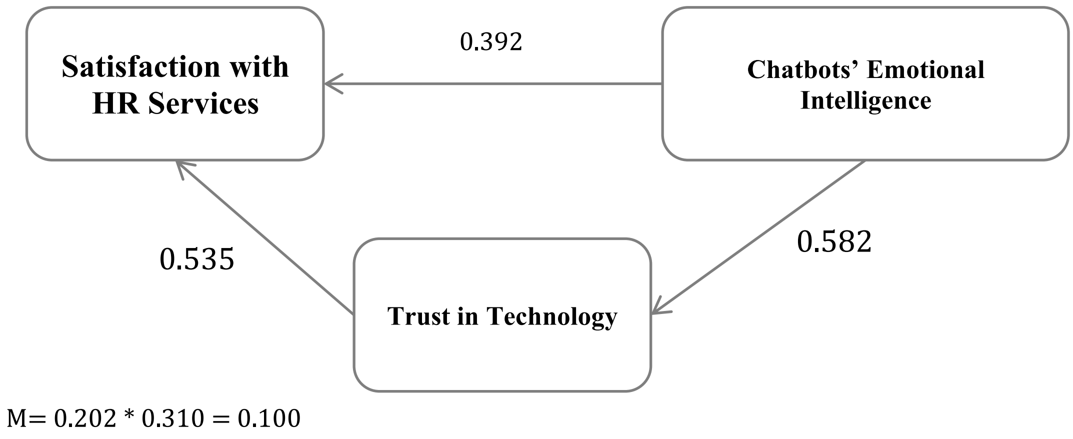

Figure 3. Summary of the relationship among employee satisfaction with HR services, artificial emotional intelligence of the chatbot, and trust in technology.

Hypothesis 1: There is a significant relationship between the artificial emotional intelligence of human resource chatbots and employee satisfaction with HR services.

The path coefficient for artificial emotional intelligence of the chatbot → employee satisfaction with HR services was 0.392, and the t-statistic was calculated as 4.845. Therefore, with 95% confidence, it can be stated that this hypothesis is confirmed.

Hypothesis 2: There is a significant relationship between the artificial emotional intelligence of human resource chatbots and trust in technology.

The path coefficient for artificial emotional intelligence of the chatbot → trust in technology was 0.582, and the t-statistic was calculated as 7.314. Therefore, with 95% confidence, it can be stated that this hypothesis is confirmed.

Hypothesis 3: There is a significant relationship between the artificial emotional intelligence of human resource chatbots and employee satisfaction with HR services through the mediating role of trust in technology.

The path coefficient for artificial emotional intelligence of the chatbot → trust in technology → employee satisfaction with HR services was 0.311, and the t-statistic was calculated as 4.675. It can be stated that this hypothesis is confirmed.

In the sub-hypotheses, the relationship between the components of the artificial emotional intelligence of the chatbot, namely emotion perception and recognition, empathy and empathic response, and emotion regulation in interaction, with employee satisfaction with HR services and trust in technology was examined. The results of examining the relationships among these variables are presented in the table below.

Table 4. Relationship Between the Components of Artificial Emotional Intelligence of the Chatbot and the Research Variables

Research Constructs	Statistic	Employee Satisfaction with HR Services	Trust in Technology
Emotion perception and recognition	Correlation coefficient	0.152	0.424
Emotion perception and recognition	Significance value	0.030	0.000
Empathy and empathic response	Correlation coefficient	0.394	0.353
Empathy and empathic response	Significance value	0.000	0.000
Emotion regulation in interaction	Correlation coefficient	0.298	0.281
Emotion regulation in interaction	Significance value	0.000	0.002

The correlation coefficient between emotion perception and recognition and employee satisfaction with HR services was 0.152, and the significance value was calculated as 0.030. Therefore, there is a positive and significant relationship between these two variables.

The correlation coefficient between emotion perception and recognition and trust in technology was 0.424, and the significance value was calculated as 0.000. Therefore, there is a positive and significant relationship between these two variables.

The correlation coefficient between empathy and empathic response and employee satisfaction with HR services was 0.394, and the significance value was calculated as 0.000. Therefore, there is a positive and significant relationship between these two variables.

The correlation coefficient between empathy and empathic response and trust in technology was 0.353, and the significance value was calculated as 0.000. Therefore, there is a positive and significant relationship between these two variables.

The correlation coefficient between emotion regulation in interaction, including tension reduction and support, and employee satisfaction with HR services was 0.298, and the significance value was calculated as 0.000. Therefore, there is a positive and significant relationship between these two variables.

The correlation coefficient between emotion regulation in interaction, including tension reduction and support, and trust in technology was 0.281, and the significance value was calculated as 0.002. Therefore, there is a positive and significant relationship between these two variables.

The outer section, or measurement model, indicates that the items considered for measuring each of the main factors have sufficient validity. The strength of the relationship between the items and their corresponding factors is assessed through factor loadings, and their significance is evaluated using the t-statistic. The results of the outer model, or measurement model, are presented in Table 5.

Table 5. Results of the Outer Section: Measurement Model

Items	Factor Loading	t-Statistic
Security and privacy → trust in technology	0.874	35.097
Predictability → trust in technology	0.858	35.930
Integrity and transparency → trust in technology	0.432	4.167
Reliability → trust in technology	0.662	8.443
Efficiency → trust in technology	0.739	10.251
Emotion regulation in interaction → artificial emotional intelligence of the chatbot	0.882	36.457
Empathy and response → artificial emotional intelligence of the chatbot	0.917	51.357
Emotion perception and recognition → artificial emotional intelligence of the chatbot	0.427	4.232
Quality → employee satisfaction with HR services	0.752	10.338
Speed → employee satisfaction with HR services	0.829	22.523
Ease and usefulness → employee satisfaction with HR services	0.840	29.493

The observed factor loadings were close to 0.60, and the t-statistics were greater than 1.96. Therefore, the outer model, or measurement model, is confirmed.

Convergent validity indicates the extent to which the variables of a construct are aligned with one another. If the estimated average variance extracted (AVE) is greater than 0.50, the constructs of the measurement model have convergent validity. To examine the reliability of each construct, rho coefficient, composite reliability (CR), and Cronbach's alpha were estimated. The convergent validity and reliability of the research constructs are presented in Table 6.

Table 6. Convergent Validity and Reliability of the Research Constructs

Main Constructs	AVE	Cronbach's Alpha	Composite Reliability (CR)	Rho Coefficient
Trust in technology	0.511	0.879	0.901	0.901
Employee satisfaction with HR services	0.586	0.799	0.849	0.806
Artificial emotional intelligence of the chatbot	0.540	0.742	0.804	0.813

The average variance extracted (AVE) for each construct is greater than 0.50; therefore, convergent validity is established. Cronbach's alpha, rho coefficient, and composite reliability (CR) for all constructs are also greater than 0.70; therefore, reliability is confirmed.

Discriminant validity is another criterion indicating that the items of one construct do not overlap with the items of other research constructs. The discriminant validity matrix is presented in Table 7.

Table 7. Discriminant Validity Assessment Matrix

Research Constructs	Trust	Satisfaction	Emotional Intelligence
Trust in technology	0.641		
Employee satisfaction with HR services	0.763	0.821	
Artificial emotional intelligence of the chatbot	0.582	0.703	0.783

Based on Table 7, the values on the main diagonal are greater than their correlations with the other constructs in the model; therefore, discriminant validity is established. After confirming the measurement models through reliability, convergent validity, and discriminant validity tests, the results obtained from the outer model can be reported.

Effect size (F^2) indicates the extent of change that independent variables exert on dependent variables. In fact, this index shows how much change occurs in the dependent variable if an independent variable is removed. This index was introduced by Cohen. Values of 0.02, 0.15, and 0.35 are considered weak, moderate, and large, respectively. The effect size values are presented in Table 8.

Table 8. Effect Size of the Research Constructs

Relationship	Effect Size	Interpretation
Artificial emotional intelligence of the chatbot → trust in technology	0.511	Strong
Trust in technology → employee satisfaction with HR services	0.600	Strong
Artificial emotional intelligence of the chatbot → employee satisfaction with HR services	0.321	Strong

In none of the above cases was the effect size lower than 0.02, and in all cases, it was estimated to be between moderate and strong.

The coefficient of determination (R^2) is estimated for endogenous constructs. The coefficient of determination indicates the extent to which changes in dependent variables are explained by independent variables. The higher the coefficient of determination for the endogenous constructs of the model, the better the model fit. Values of 0.19, 0.33, and 0.67 are considered the benchmark values for weak, moderate, and strong fit of the structural section of the model based on the coefficient of determination criterion. The coefficient of determination (R^2) and adjusted coefficient of determination are reported in Table 9.

Table 9. Coefficient of Determination and Adjusted Coefficient of Determination

Main Constructs	Coefficient of Determination	Adjusted Coefficient of Determination	Interpretation
Trust in technology	0.338	0.334	Moderate
Employee satisfaction with HR services	0.684	0.680	Strong

Based on the results of Table 9, the coefficient of determination for the endogenous constructs of the research model is desirable. The coefficient of determination for the trust construct was estimated at 0.338, which is a moderate value. The coefficient of determination for the employee satisfaction with HR services construct was estimated at 0.680, which is a strong value. This indicates that the model variables were able to explain 33% of the changes in trust in technology and 68% of the changes in employee satisfaction with HR services. The coefficient of determination and the adjusted coefficient of determination for the endogenous constructs are very close to each other, indicating that the model has appropriate predictive power and that the coefficient of determination can be trusted.

Collinearity is a condition indicating that an independent variable is a linear function of other independent variables. If collinearity in a regression equation is high, it means that there is a high correlation among the independent variables, and despite a high coefficient of determination, the predictive power of the model may be invalid.

Table 10. Variance Inflation Factor Statistic: Collinearity of the Research Constructs

Relationship	Collinearity
Artificial emotional intelligence of the chatbot → trust in technology	1.000
Trust in technology → employee satisfaction with HR services	1.511
Artificial emotional intelligence of the chatbot → employee satisfaction with HR services	1.500

The variance inflation factor (VIF) statistic is used to examine the degree of collinearity. This statistic indicates the extent to which changes in the estimated coefficients have increased due to collinearity. Based on a rule of thumb proposed by Kutner et al. (2004), if VIF is greater than 10, collinearity is high. However, as Sheather has also emphasized, in most cases, the threshold intensity is considered to be 5. The variance inflation factor statistic was estimated to be less than 5, indicating that the structural model has good adequacy.

The predictive relevance index (Q^2) is also used to assess the predictive power of the model. This index was introduced by Stone and Geisser and is estimated using the blindfolding method. If the value of Q^2 is positive, it indicates that the model has appropriate predictive ability. In addition, the q² value estimates the relative effect of the predictive relevance index. Here again, values of 0.02, 0.15, and 0.35 are used to evaluate weak, moderate, and large adequacy, respectively. The predictive relevance index (Q^2) is reported in Table 11.

Table 11. Predictive Relevance Index and Relative Effect of the Predictive Relevance Index

Main Constructs	Q^2	q^2	Interpretation
Trust in technology	0.314	0.120	Moderate
Employee satisfaction with HR services	0.238	0.231	Moderate

The Q^2 index was positive in all cases; therefore, the model has appropriate predictive capability.

To evaluate model fit, the GOF, RMS_theta, SRMR, and NFI indices are used. For the GOF index, values of 0.01, 0.25, and 0.36 have been introduced as weak, moderate, and strong values, respectively. For the RMS_theta index, values below 0.12 indicate model adequacy, whereas higher values indicate lack of adequacy. The SRMR index should preferably be below 0.10 and, under a stricter criterion, below 0.08.

Table 12. Evaluation of Model Fit

Index	GOF	RMS_theta	SRMR	NFI	Normed Chi-Square
Acceptable value	Greater than 0.36	Less than 0.12	Less than 0.08	Greater than 0.60	Less than 5
Estimated value	0.292	0.101	0.051	0.817	1.523

In this study, the GOF index was estimated at 0.292, close to 0.36; the RMS_theta index was estimated at 0.101, lower than 0.12; the SRMR index was estimated at 0.051, lower than 0.08; the NFI index was estimated at 0.817, greater than 0.60; and the normed chi-square index was estimated at 1.523, lower than 5. Therefore, the model has good fit.

4. Discussion and Conclusion

The present study examined the mechanism of trust in technology in the relationship between the artificial emotional intelligence of human resource (HR) chatbots and employees’ satisfaction with HR services among employees of the Science and Research Branch, Tehran. The findings demonstrated that artificial emotional intelligence of HR chatbots has a significant positive relationship with employee satisfaction with HR services. Furthermore, artificial emotional intelligence was found to have a significant positive relationship with trust in technology. The results also indicated that trust in technology plays a significant mediating role in explaining the relationship between artificial emotional intelligence and employee satisfaction with HR services. In addition, the analysis of the dimensions of artificial emotional intelligence showed that emotion perception and recognition, empathy and empathic response, and emotion regulation during interaction all had significant positive relationships with both trust in technology and employee satisfaction with HR services. Overall, the results suggest that emotionally intelligent HR chatbots can improve employees’ experiences of HR services directly and indirectly through the enhancement of trust in technological systems.

The first finding of the study revealed a significant positive relationship between the artificial emotional intelligence of HR chatbots and employee satisfaction with HR services. This finding suggests that when HR chatbots demonstrate greater capabilities in understanding emotions, responding empathetically, and managing emotional interactions, employees evaluate HR services more positively. The result can be explained through the increasingly service-oriented nature of HRM in digital environments. Employees often interact with HR systems to resolve concerns, obtain information, seek support, or address administrative issues. Under such circumstances, the emotional quality of communication becomes an important determinant of perceived service effectiveness. When chatbot systems recognize emotional cues and provide supportive responses, employees are more likely to perceive the interaction as meaningful, helpful, and user-centered. Consequently, satisfaction with HR services increases because employees experience not only functional assistance but also psychological reassurance.

This finding is consistent with the broader literature emphasizing the importance of conversational AI quality and user experience. Research has shown that chatbot interactions influence user behavior, compliance, and service evaluations, particularly when users perceive the system as responsive and supportive (Adam et al., 2021). Similarly, future directions in chatbot research emphasize the importance of social and emotional dimensions of human–chatbot interaction rather than focusing solely on technical functionality (Følstad et al., 2021). The finding is also consistent with recent discussions on generative conversational AI, which suggest that advanced AI systems are increasingly valued for their ability to engage in context-sensitive and human-like interactions that improve user experiences (Dwivedi et al., 2023). In the HR context, emotionally intelligent chatbot interactions appear to strengthen the perceived quality, accessibility, and usefulness of HR services, thereby enhancing employee satisfaction.

The second major finding demonstrated that artificial emotional intelligence has a significant positive effect on trust in technology. This result highlights the importance of emotional interaction quality in shaping employees' perceptions of technological systems. Trust is often formed when users perceive a technology as competent, reliable, predictable, and aligned with their needs. Emotional intelligence contributes to these perceptions by reducing uncertainty and creating a sense of interpersonal understanding during human–technology interaction. When employees perceive that a chatbot can recognize emotions, provide empathetic responses, and adapt its communication style appropriately, they are more likely to regard the system as trustworthy. In other words, emotional intelligence functions as a signal that the technology is capable of understanding users rather than merely processing information.

This finding aligns closely with prior studies on trust in artificial intelligence. Research reviewing empirical evidence on human trust in AI concluded that trust is strongly influenced by user perceptions of competence, reliability, transparency, and interaction quality (Glikson & Woolley, 2020). Likewise, explainability and causability have been shown to enhance trust and acceptance of AI systems by helping users understand and predict system behavior (Shin, 2021). The present findings extend this literature by suggesting that emotional intelligence may represent an additional mechanism through which trust develops. While explainability addresses the cognitive foundations of trust, emotional intelligence appears to strengthen its affective foundations. Employees may trust emotionally intelligent HR chatbots not only because they provide accurate information but also because they create a more supportive and reassuring interaction experience.

Another important finding of the study was the significant mediating role of trust in technology in the relationship between artificial emotional intelligence and employee satisfaction with HR services. This result suggests that emotionally intelligent chatbot systems improve employee satisfaction partly because they increase trust in technology. The finding supports the notion that satisfaction is not determined solely by technological performance but also by employees' confidence in the technology delivering the service. Employees who trust HR chatbots are more likely to rely on them, perceive their recommendations as useful, and view interactions as beneficial. Consequently, trust serves as a psychological mechanism that transforms positive perceptions of chatbot emotional intelligence into higher levels of satisfaction with HR services.

This result is consistent with theoretical and empirical work emphasizing trust as a prerequisite for successful AI adoption and technology acceptance. Studies of AI-enabled HRM have repeatedly argued that technological innovations generate value only when employees are willing to accept and use them effectively (Tambe et al., 2019; Vrontis et al., 2022). Similarly, research on digital HRM has emphasized that technological systems influence organizational outcomes through employees' perceptions and experiences rather than through technical capabilities alone (Strohmeier, 2020). The mediating role of trust identified in the present study supports these perspectives and suggests that organizations seeking to improve employee satisfaction through AI-based HR services should focus not only on functionality but also on trust-building features such as transparency, privacy protection, reliability, and emotionally appropriate interaction design.

The findings regarding the individual dimensions of artificial emotional intelligence provide additional insights. The positive relationship between emotion perception and recognition and both trust in technology and employee satisfaction indicates that employees value chatbot systems capable of identifying and understanding their emotional states. Emotion recognition enhances the relevance and appropriateness of responses, making interactions feel more personalized and meaningful. Employees may interpret such capabilities as evidence that the system is attentive to their concerns and capable of providing appropriate support. As a result, they develop more positive attitudes toward both the technology and the HR services it delivers.

The positive association between empathy and empathic response and the study outcomes further highlights the importance of relational qualities in digital HR interactions. Empathetic communication helps employees feel understood, respected, and supported. This finding is particularly important in HR contexts because many employee inquiries involve personal, professional, or organizational concerns. An empathic chatbot can partially replicate some of the supportive characteristics traditionally associated with human HR representatives. The result aligns with emerging discussions suggesting that AI systems increasingly need to complement technical intelligence with social and emotional capabilities to improve user acceptance and service effectiveness (Dwivedi et al., 2023; Følstad et al., 2021). By demonstrating empathy, HR chatbots may reduce perceptions of impersonality and strengthen employees' emotional engagement with digital HR services.

Similarly, the positive relationship between emotion regulation during interaction and both trust and satisfaction indicates that employees value chatbot systems capable of reducing tension, managing frustration, and providing supportive guidance during difficult interactions. HR-related issues often involve uncertainty, procedural complexity, or workplace concerns that can generate stress. A chatbot capable of regulating emotional interactions can help maintain constructive communication and improve the overall user experience. This finding may also be interpreted in light of concerns regarding organizational dehumanization associated with AI adoption. Research has warned that AI in HRM can create negative employee reactions when technological systems are perceived as replacing human concern and interpersonal care (Shin et al., 2025). The ability of chatbots to regulate emotions and provide support may mitigate these concerns by making digital interactions feel more human-centered and considerate.

The broader implications of the findings are also consistent with contemporary perspectives on AI-enabled HR transformation. Scholars have argued that AI is redefining HR functions by improving service delivery, talent management, organizational adaptability, and strategic decision-making (Sharifi et al., 2025; Subrahmanyam, 2025; Tak, 2025). The present study suggests that emotional intelligence should be considered an essential component of this transformation. Technological sophistication alone may not be sufficient to ensure successful implementation. Rather, AI systems must be capable of creating positive psychological experiences that encourage trust, acceptance, and satisfaction. This interpretation is supported by research highlighting the importance of human-centered AI implementation in healthcare, Industry 5.0 environments, and digitally transformed organizations (Temjanovski et al., 2025; Thomas et al., 2026).

The findings also support recent research emphasizing the strategic importance of AI integration within HR systems. Studies have shown that AI applications can improve organizational agility, resilience, and service effectiveness when implemented appropriately (Sadeghi et al., 2025). At the same time, researchers have noted that AI implementation requires careful consideration of organizational, ethical, and behavioral factors (Moghadam et al., 2025). The present study contributes to this discussion by demonstrating that trust and emotional intelligence represent two critical behavioral dimensions that influence employee reactions to AI-enabled HR services. Organizations that neglect these dimensions may fail to achieve the full benefits of AI adoption despite investing in advanced technological infrastructure.

Finally, the study reinforces the importance of employee-centered approaches to AI implementation. AI-based HR training and organizational readiness have been identified as essential factors in ensuring successful adoption and acceptance of intelligent systems (Orhan & Kurnaz, 2025). The positive relationships observed in this study suggest that employees respond favorably when AI systems are designed to understand emotions, provide empathic support, and foster trust. Consequently, HR chatbot development should not be guided solely by efficiency objectives but also by the goal of enhancing employee experiences and strengthening organizational relationships. By integrating emotional intelligence capabilities into chatbot design, organizations may create more trusted, accepted, and satisfying digital HR environments.

Several limitations should be considered when interpreting the findings of this study. First, the research was conducted within a single university, which may limit the generalizability of the findings to other organizational settings, industries, or cultural contexts. Second, the study employed a cross-sectional design, making it difficult to establish causal relationships among the variables. Third, all data were collected using self-report questionnaires, which may be subject to common method bias and social desirability effects. Fourth, employees' perceptions of chatbot emotional intelligence, trust, and satisfaction may be influenced by individual characteristics that were not examined in the present study. Finally, the study focused on perceived chatbot capabilities rather than actual interaction data, which may differ from employees' real experiences during chatbot use.

Future studies should examine the proposed relationships in different organizational contexts, including private companies, public organizations, healthcare institutions, and multinational enterprises. Longitudinal and experimental designs could provide stronger evidence regarding causal relationships among artificial emotional intelligence, trust in technology, and employee satisfaction. Researchers may also investigate additional mediating and moderating variables such as technology readiness, perceived usefulness, organizational support, digital literacy, and employee personality characteristics. Comparative studies between AI chatbots and human HR representatives could provide valuable insights into the relative importance of emotional intelligence in digital and human service encounters. Furthermore, future research may benefit from incorporating behavioral data, chatbot interaction logs, and objective service-performance indicators alongside perceptual measures.

Organizations intending to implement HR chatbots should prioritize emotional intelligence capabilities during system design and deployment. Chatbots should be developed to recognize emotional cues, provide empathic responses, and support employees during stressful interactions. HR departments should also establish transparent communication regarding chatbot functions, data privacy protections, and service limitations to strengthen trust in technology. Continuous monitoring of employee experiences and satisfaction can help organizations identify areas for improvement and refine chatbot performance. Training programs should be provided for both employees and HR professionals to encourage effective use of AI-enabled HR services. Finally, organizations should view HR chatbots as tools that complement rather than replace human support, ensuring that employees retain access to human assistance when complex or sensitive issues arise.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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