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Design and Explanation of an Artificial-Intelligence-Based Human Resource Management Model

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ABSTRACT

The purpose of this article is to design and explain a human resource management model based on artificial intelligence technology. The present study is a developmental and applied research project; however, given the research procedure, it incorporates a combination of documentary, descriptive, and causal research methods. In this study, library and internet sources—including books, articles, and case studies—as well as field studies, specifically interviews with experts and specialists, were used to propose, design, and validate an AI-based human resource management model. The collected data were analyzed using MAXQDA software. The results of data analysis in the qualitative phase led to the extraction of an appropriate model for AI-based human resource management. The extracted model includes five main dimensions, twelve core categories, and fifty-one subcategories or indicators. In the structural modeling section, the model was examined and validated through MICMAC software, and the results indicate that the variable "process and policy optimization using intelligent algorithms and models" has the highest level of influence. Moreover, the variable "optimization of communication structures and establishment of organizational justice" ranks second in terms of influence. Finally, the variables "assessment and prediction of employee motivation and behavior" rank third, "forward-looking planning for learning, growth, and innovation in the organization" rank fourth, and "performance evaluation and improvement through e-learning" rank fifth in influencing the AI-based human resource management model.

Keywords: model design, human resource management, artificial intelligence, futures studies

Introduction

The accelerating diffusion of artificial intelligence (AI) across organizational functions has fundamentally reshaped managerial practices, workforce expectations, and the strategic orientation of human resource management (HRM). Contemporary organizations increasingly recognize that traditional HRM mechanisms—designed for industrial-era stability—are insufficient for addressing the volatility, data-intensity, and algorithmic complexity defining modern enterprises. This transition is evidenced by a global surge in AI-enabled HRM applications, ranging from automated recruitment and predictive performance analytics to adaptive learning systems and AI-based decision-support mechanisms, reflecting the broader paradigm shift toward digitally augmented organizational capabilities [1-4]. The emergence of AI-HRM integration has consequently stimulated scholarly debates concerning its implications for workforce empowerment, skill development, job satisfaction, decision accuracy, and organizational resilience.

Historical foundations in HRM, such as those rooted in the Human Relations Movement, emphasized social dynamics, interpersonal connections, and participatory management as essential drivers of employee performance [1]. While these principles remain relevant, modern organizations contend with unprecedented volumes of workforce data, requiring analytical capabilities far beyond human cognitive limits. AI systems enable rapid detection of behavioral patterns, prediction of employee turnover, automated identification of training needs, and optimized allocation of human capital resources [5-7]. As a result, AI is no longer viewed merely as a technological tool but as a strategic partner that redefines how HRM concepts such as performance evaluation, engagement, and organizational learning are conceptualized and operationalized.

The digital transformation of HRM is further reinforced by empirical evidence showing that advanced data-driven HRM practices significantly enhance organizational performance. For example, high-performance work systems have been shown to reduce burnout and improve job satisfaction by enabling employees to connect more meaningfully with their professional environments [8]. In parallel, sustainable HRM frameworks emphasize employee well-being, ethical treatment, and long-term workforce development—dimensions that AI can augment by ensuring consistent, evidence-based decision-making [9, 10]. These developments point to a broader shift from administrative HRM toward strategic, intelligence-driven HRM.

One of the most transformative contributions of AI lies in its capacity to synthesize and interpret massive data sets related to employee performance, behavior, competencies, motivations, and learning trajectories. AI-powered analytics—particularly through machine learning, natural language processing, and predictive modeling—offer organizations unprecedented foresight into workforce trends and risks. Studies highlight that these capabilities not only enhance decision quality but also reduce bias, ensure greater equity, and strengthen accountability within HR practices [11-13]. Furthermore, AI supports dynamic workforce planning through continuous monitoring of skill gaps, forecasting of future talent needs, and identifying high-potential employees for leadership pipelines [14-16].

AI also significantly influences employee empowerment and organizational commitment. Meta-analytic research shows that data-supported decision-making structures encourage employee autonomy while reinforcing trust and clarity in managerial actions [12]. Likewise, algorithmic systems that enhance communication, improve workflow transparency, and facilitate timely feedback contribute to higher engagement and organizational citizenship behaviors [17, 18]. These findings underscore AI's potential to elevate HRM from a reactive administrative function to an anticipatory system capable of shaping future organizational competencies.

The integration of AI into HRM also aligns closely with contemporary conceptions of dynamic capabilities and strategic flexibility. As organizations navigate turbulent environments marked by pandemics, supply chain disruptions, and technological uncertainties, the strategic use of AI allows them to remain adaptive, resilient, and competitive. Leadership research during crises such as COVID-19 demonstrates that HR development capabilities—including digital learning, remote workforce management, and AI-supported collaboration—play a critical role in organizational survival [19]. These capabilities are strengthened when organizations embed AI into their HRM processes, enabling real-time decision-making, remote engagement strategies, and automated support systems [20-22].

Furthermore, AI-driven HRM has emerged as an essential factor in shaping supply chain agility, workforce resilience, and organizational innovation. Recent studies emphasize that strategic HRM combined with AI elevates information responsiveness, promotes cross-functional collaboration, and strengthens employee adaptability—key determinants of resilience in complex operational systems [21, 22]. Organizations that integrate AI into workforce planning show enhanced capability to sense, interpret, and respond to emerging risks, thereby contributing to sustainable competitive advantage [20, 23].

Parallel advancements highlight that AI enhances recruitment and performance management systems by improving candidate-job matching, optimizing competency assessment, and identifying predictors of long-term success [24, 25]. These systems enable HR managers to transition from intuition-based assessments to evidence-based workforce design. Furthermore, AI-supported diversity, equity, and inclusion (DEI) analytics help organizations detect patterns of bias, evaluate fairness in promotions, and monitor equitable distribution of opportunities [11]. This analytical precision ensures that HR decisions reflect organizational values and ethical standards.

Nevertheless, the expanding role of AI introduces complex challenges. Scholars warn that algorithmic opacity, inadequate data governance, and insufficient HR digital literacy may undermine the accuracy and fairness of AI-driven decisions [2, 26]. Ethical debates surrounding AI in HRM frequently raise concerns about surveillance, privacy, consent, and deskilling, suggesting the need for clear regulatory and organizational frameworks [6, 27]. Simultaneously, global disparities in data infrastructure and AI maturity levels contribute to uneven adoption across sectors and regions [7, 28]. Therefore, while AI offers transformative potential, its integration must be thoughtful, systematic, and aligned with organizational culture and long-term strategy.

A related challenge concerns the readiness of employees to engage with AI-enabled HRM systems. Organizational learning research suggests that employees require a growth mindset, digital literacy, and adaptive capabilities to benefit fully from AI-driven interventions [16]. Moreover, the shift toward algorithmic decision-making raises concerns regarding employee trust, acceptance, and psychological safety [8, 29]. As a result, HR leaders must prioritize transparent communication, participatory implementation, and continuous training to ensure that AI tools are perceived as supportive rather than punitive mechanisms.

Universities, public institutions, and private enterprises have also begun exploring frameworks for sustainable HRM grounded in AI-driven foresight. Research documenting HRM sustainability highlights the importance of resource efficiency, employee well-being, and long-term workforce development [6, 9]. AI enables these objectives by providing predictive analytics, personalized learning pathways, and real-time insights into workforce dynamics. Futures studies in management demonstrate that AI-supported scenario planning enhances strategic preparedness and mitigates uncertainty in talent management systems [10]. Consequently, organizations are increasingly adopting AI-based HRM models that combine predictive analytics with strategic foresight to build agile, resilient, and future-ready human capital systems [30, 31].

In addition, emerging scholarship has emphasized the role of AI in strengthening global HRM effectiveness by leveraging competitive intelligence, social media analytics, and digital ecosystems [18, 28]. AI-enabled sensing capabilities enhance recruitment branding, improve employee engagement, and support data-informed leadership development. Scholars also note that AI technologies enable HRM systems to align more closely with organizational values, strategic priorities, and environmental sustainability objectives [20, 23]. In this sense, AI acts not only as a technological tool but also as a catalyst for organizational transformation, innovation, and continuous improvement.

Despite the abundance of studies on AI applications in HRM, there remains a pressing need for a comprehensive model that integrates predictive analytics, behavioral insights, communication structures, diversity evaluation, and future-oriented workforce planning into a unified framework. Traditional HRM models do not capture the multi-layered, interconnected nature of AI-enabled HR functions, nor do they adequately address how AI can optimize structural relationships, improve organizational justice, or strengthen long-term learning and innovation capabilities. Moreover, scholars increasingly call for HRM frameworks that reflect ethical considerations, system-wide integration, and strategic foresight [7, 19, 32].

Given these conceptual gaps, this study seeks to bridge theory and practice by developing an empirically grounded, future-oriented AI-based HRM model derived from thematic analysis, Delphi expert consensus, and structural modeling techniques. Therefore, the aim of this study is to design and validate a comprehensive human resource management model based on artificial intelligence using a futures-studies approach.

Methodology

The present study employs a mixed-methods research design in which quantitative and qualitative methods are used concurrently. In this research, by reviewing an extensive theoretical foundation, an appropriate framework for investigating and examining the research problem has been developed. From the perspective of purpose, the study is *qualitative–exploratory*, and an initial model is designed using *thematic analysis*. In the qualitative phase, thematic analysis and in-depth interviews with experts were first conducted, followed by coding related to this stage. In the next stage, the output of the thematic analysis was examined using the Delphi method by relevant experts, and in order to complete the futures-studies process, the method of *cross-impact analysis* was used to identify the strategic variables of the research.

In the quantitative section, the Delphi approach and scenario writing were applied to validate the model proposed in the previous phase and to outline future-oriented scenarios of the model. The statistical population consists of managers and employees in the banking industry, with different sample groups for the qualitative and quantitative stages. In the qualitative phase, purposive sampling was used—sampling continued until theoretical saturation was reached, ultimately including 15 university professors in the field of human resources and banking-industry managers. In the quantitative phase, 16 university professors and banking-industry managers participated in the Delphi stage. Additionally, after presenting the scenarios, 10 academic experts participated in the scenario-writing stage. Data collection methods in both qualitative and quantitative phases include library and field methods. Data analysis is conducted in two qualitative and quantitative sections. In the qualitative section, thematic analysis and interviews as the data-collection tool are employed to identify the factors and components influencing AI-based human resource management in Iran, whereas in the quantitative phase, *confirmatory factor analysis* and *structural equation modeling* are used to examine the relationships between the variables.

Findings and Results

Open Coding: In this phase, the concepts and categories presented in the expert interviews were identified and extracted. The initial results of open coding are presented in the tables below:

Table 1

Results of Open Coding

Interview Text	Extracted Code
Algorithms help us recognize behavioral patterns and individual productivity more accurately.	AI-based performance analysis
Sometimes employees have capabilities that traditional evaluations fail to detect, but algorithms identify them.	Talent discovery through data mining
Chatbots have reduced the workload of the HR unit and improved the user experience.	Automation of HR interactions
By analyzing behavioral data, we can determine who may soon resign.	Turnover prediction
The system screens résumés automatically and recommends the best candidates with minimal human intervention.	Intelligent résumé-job matching
By examining tone and vocabulary, we understand employee satisfaction levels or signs of burnout.	Employee sentiment analysis

The system categorizes complaints automatically to facilitate faster handling.	Complaint classification with NLP
Each employee has a unique path designed for them based on data.	Personalized career-path design
The system weights criteria and suggests optimal options.	Decision-making based on intelligent models
Training needs are extracted from individual performance data, not speculation.	Training design based on performance analysis
Employees are grouped based on behavioral and performance similarities.	Employee clustering based on behavioral characteristics
When absence levels exceed typical thresholds, the system issues an alert.	Absence-pattern detection with AI
Team data show which managers have performed better.	Manager performance evaluation through algorithms
Algorithms reveal which teams require intervention.	Optimization of team interactions with data analysis
The system identifies reasons for resignation by examining exit data.	Attrition-cause analysis
By examining messages and reports, conflicts are identified more quickly.	Conflict management with data analysis
The system assesses employee emotions and satisfaction instantaneously.	Real-time employee satisfaction monitoring
Learning pathways are suggested based on performance and interests.	Skill-development pathway recommendations
The system learns which processes yield the best outcomes.	Process optimization via reinforcement learning
Communication and behavioral data reveal the organization's prevailing culture.	Organizational culture analysis using data mining
The system learns which processes yield the best outcomes.	Process optimization via reinforcement learning
Communication and behavioral data reveal the organization's prevailing culture.	Organizational culture analysis using data mining
The system suggests appropriate courses based on individual needs.	Training recommender system
Systems make decisions based on data, not human prejudice.	Reducing hiring bias through AI
Team performance data indicate where improvements are needed.	Team productivity analysis
When signs of chronic fatigue appear, the system issues an alert.	Burnout detection with data analysis
The system predicts what skills will be needed in the future.	Human-resource needs forecasting
The system reveals who the communication hubs are and where disconnects exist.	Organizational communication-network analysis
The time required for résumé screening and interviews has significantly decreased.	Acceleration of recruitment through AI
The system shows which courses truly improved performance.	Training-effectiveness analysis using data mining
The system can identify indicators of unethical behavior.	Ethical-behavior analysis via algorithms
The system warns where an HR crisis may occur.	HR risk analysis
The system suggests which structure maximizes productivity.	Data-driven organizational-structure design
Data reveal how diverse the organization actually is.	Organizational diversity analysis
The system categorizes and analyzes feedback for better decision-making.	Employee feedback analysis
Algorithms show who holds critical roles in the organization.	Key-employee identification
The system identifies factors contributing to faster promotion.	Promotion-path analysis
Data reveal which employees experience imbalance.	Work-life balance analysis
The system shows which policies have been effective.	HR policy evaluation
The system shows who is more active and who is more passive.	Employee engagement analysis
The system shows how much of the training content has been internalized.	Employee-learning monitoring
The system shows how aligned employees are with organizational culture.	Value-alignment analysis
The system shows which meetings were useful and which were not.	Meeting-effectiveness analysis
The system shows which units collaborate more effectively.	Analysis of inter-unit interaction
The system suggests promotion based on performance and data.	Automated data-driven promotion
The system shows whether the individual is placed in the right role.	Job-fit analysis
The system shows what factors increase or decrease motivation.	Employee-motivation analysis
The system shows who is more likely to stay.	Organizational-loyalty analysis
The system shows how the organization learns from past experiences.	Organizational-learning analysis
The system shows which rewards were genuinely motivating.	Reward-effectiveness analysis
The system shows how decisions are made and what outcomes they produce.	HR decision-making analysis
The system shows where ambiguity exists and requires correction.	Process-transparency analysis
The system shows how each individual progresses along their growth path.	Individual-development analysis
The system shows whether promotions were equitable.	Promotion-fairness analysis
The system shows whether evaluations were accurate and effective.	Performance-evaluation effectiveness analysis
The system shows who contributes to organizational innovation.	Innovation-participation analysis
The system shows how aligned employees are with the organization's mission.	Value-alignment analysis
The system shows where communication is more effective.	Communication-effectiveness analysis
The system shows who participates in decision-making.	Participation-in-decision-making analysis
The system shows which benefits are most preferred.	Benefits-satisfaction analysis

The results of the coding analysis in the open-coding stage show that 62 codes or subthemes were extracted from the expert interviews. These subthemes were categorized in the next stage.

Axial Coding: In this stage, axial coding is performed. In fact, indicators that share a common axis are grouped into appropriate axial codes.

Table 2

Results of Open and Axial Coding

Axial Codes (Main Themes)	Open Codes (Subthemes)
Performance improvement through intelligent behavioral data	Team productivity analysis, effectiveness analysis of performance evaluation, AI-based performance analysis
Learning assessment and effectiveness through educational data	AI-based training effectiveness evaluation, analysis of individual development in the AI pathway, AI-based meeting effectiveness analysis, employee learning analysis
Identification of high-risk behaviors and prediction of employee turnover or reduced motivation with AI predictive tools	Turnover prediction, turnover-cause analysis, human-resource risk analysis, organizational loyalty analysis, burnout detection, employee-motivation analysis
Use of intelligent algorithms to facilitate and accelerate HR processes	HR-interaction automation, recruitment acceleration, automated data-driven promotion, process optimization via reinforcement learning, intelligent-model-based decision-making
Deriving insights from employee behavior, emotions, and interactions based on AI recommender systems	Employee sentiment analysis, ethical-behavior analysis, employee-feedback analysis, real-time satisfaction monitoring, employee-engagement analysis, participation-in-decision-making analysis
Creating growth and learning pathways tailored to employee characteristics based on AI recommender systems	Personalized career-path design, skill-development pathway recommendations, training recommender system, promotion-path analysis, job-fit analysis
Understanding organizational communication structures and prevailing values based on AI recommender systems	Organizational-culture analysis through data mining, organizational-communication-network analysis, inter-unit interaction analysis, value-alignment analysis, value-fit analysis
Assessment of equity and diversity in HR decisions and policies	Promotion-equity analysis, resource-distribution equity analysis, diversity-policy effectiveness analysis, organizational-diversity analysis, bias-reduction in recruitment
Measuring the efficiency of HR policies and operational systems based on AI recommender systems	HR-policy evaluation, reward-effectiveness analysis, motivation-effectiveness analysis, feedback-effectiveness analysis, communication-effectiveness analysis, process-transparency analysis
AI-driven forward planning in recruitment, retention, and HR development	HR-needs forecasting, data-driven organizational-structure design, HR decision-making analysis, key-employee identification
Assessing the organization’s capacity for continuous learning and innovation based on AI recommender systems	Organizational-learning analysis, innovation-participation analysis

The results of the open-coding section show that 62 codes or subcategories were identified and extracted. These concepts and subcategories, forming the basis of a suitable model for AI-based human resource management using a futures-studies approach, were derived from expert interview transcripts. In the next stage, axial coding was conducted to group these subcategories into axial codes (main themes). These main themes represent broader concepts that cluster subthemes sharing similarities in foundation, meaning, and function. The results of the axial coding show that the open codes were classified into 12 main themes.

Selective Coding: Here, the main categories are identified, consisting of 10 principal themes that are integrated into 5 overarching themes: (1) performance assessment and improvement through e-learning; (2) assessment and prediction of employee motivation and behavior; (3) optimization of processes and policies using intelligent algorithms and models; (4) optimization of processes and policies using intelligent algorithms and models (duplicate in original text); and (5) forward-looking planning for learning, growth, and innovation in the organization.

Table 3

Results of the Three Stages of Open, Axial, and Selective Coding

Selective Codes (Overarching Themes)	Axial Codes (Main Themes)	Open Codes (Subthemes)
Performance evaluation and e-learning enhancement through AI	Performance improvement through intelligent behavioral data	Team productivity analysis, performance evaluation effectiveness analysis, AI-based performance analysis
	Learning assessment and effectiveness through educational data	AI-based training-effectiveness evaluation, analysis of individual development in the AI pathway, AI-based meeting-effectiveness analysis, employee learning analysis
Assessment and prediction of employee motivation and behavior using AI tools	Identification of high-risk behaviors and prediction of employee turnover or decreased motivation using AI predictive tools	Turnover prediction, analysis of organizational disengagement, organizational loyalty analysis, burnout detection
	Use of intelligent algorithms to facilitate and accelerate HR processes	Employee-motivation analysis, human-resource risk analysis, organizational loyalty analysis
Optimization of HR processes and policies using intelligent AI algorithms and models	Deriving insights from employee behavior, emotions, and interactions based on AI recommender systems	HR-interaction automation, recruitment acceleration, automated data-driven promotion, process optimization using reinforcement learning, intelligent-model-based decision-making

	Creating growth and learning paths tailored to employee characteristics based on AI recommender systems	Employee sentiment analysis, ethical-behavior analysis, employee-feedback analysis, real-time satisfaction monitoring, employee-engagement analysis, participation-in-decision-making analysis
	Understanding organizational communication structures and dominant values using AI recommender systems	HR policy evaluation, reward-effectiveness analysis, motivation-effectiveness analysis, feedback-effectiveness analysis, communication-effectiveness analysis, process-transparency analysis
Optimization of communication structures and establishment of organizational justice using AI recommender systems	Assessment of equity and diversity in HR decisions and policies	Promotion-equity analysis, resource-distribution justice analysis, diversity-policy effectiveness analysis, organizational-diversity analysis, bias reduction in recruitment
	Measuring efficiency of HR policies and operational systems based on AI recommender systems	Organizational-culture analysis through data mining, organizational-network analysis, inter-unit interaction analysis, value-alignment analysis, value-fit analysis
Future-oriented AI planning for learning, growth, and innovation in the organization	AI-driven future planning for recruitment, retention, and HR development	Personalized career-path design, skill-development pathway suggestion, training recommender system, promotion-path analysis, job-fit analysis
	Assessing the organization’s capacity for continuous learning and innovation using AI recommender systems	HR-needs forecasting, data-driven organizational-structure design, HR decision-making analysis, key-employee identification
	Assessing the organization’s capacity for continuous learning and innovation	Organizational-learning analysis, innovation-participation analysis

The results of data analysis using MAXQDA software show that the appropriate model for AI-based human resource management, developed through a futures-studies approach, consists of five main dimensions (overarching themes):

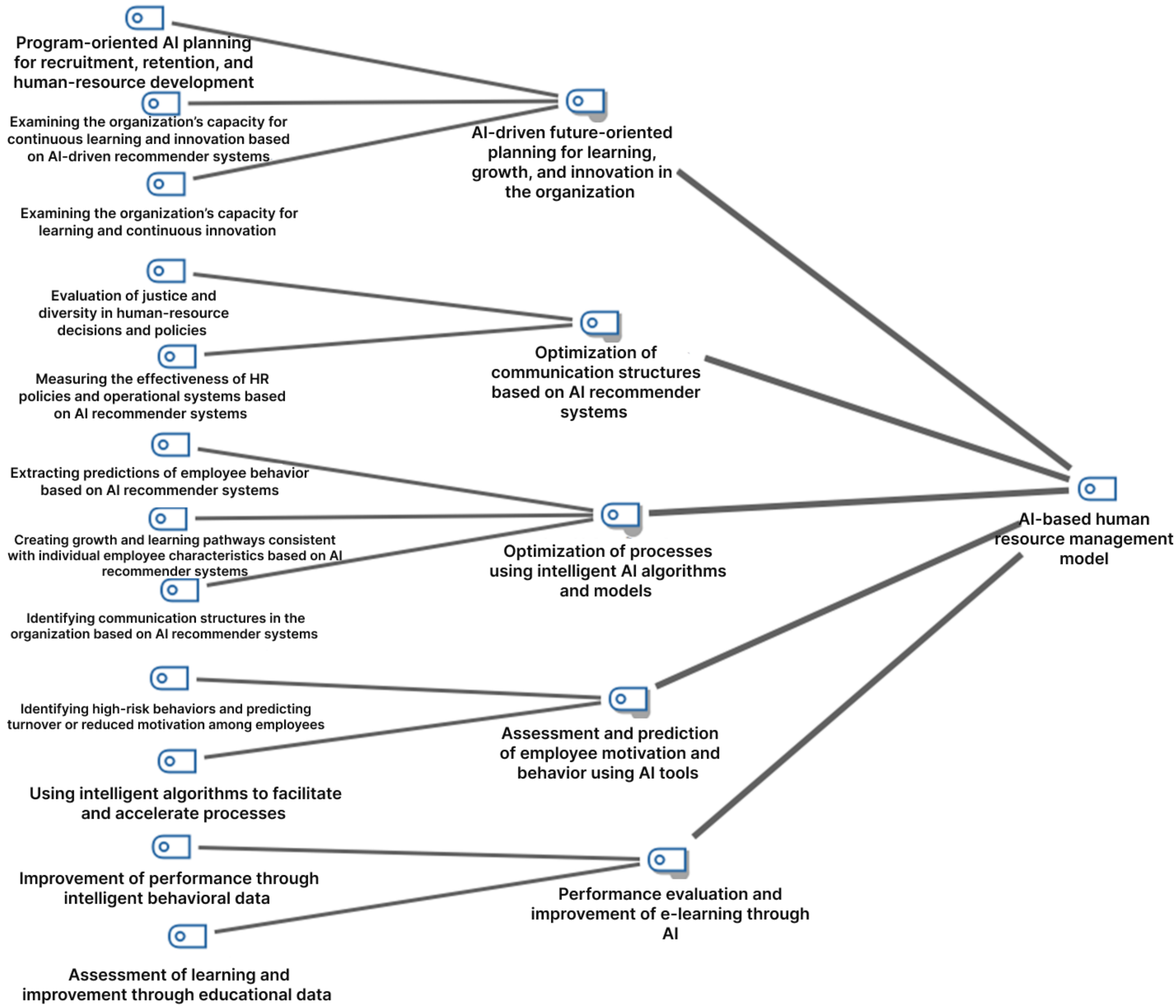
1. Performance evaluation and e-learning improvement through AI
2. Assessment and prediction of employee motivation and behavior using AI tools
3. Optimization of processes and policies using intelligent AI algorithms and models
4. Optimization of communication structures and establishment of organizational justice using AI recommender systems
5. Future-oriented AI planning for learning, growth, and innovation in the organization

These dimensions include 12 secondary indicators or subcomponents identified as main themes, which are:

1. Performance improvement through intelligent behavioral data
2. Learning assessment and effectiveness through educational data
3. Identification of harmful employee behaviors using AI predictive tools
4. Prediction and assessment of employee motivation
5. Use of algorithms to facilitate and accelerate HR processes
6. Deriving insights from employee behavior, emotions, and interactions through AI recommender–based analysis
7. Measuring the efficiency of HR policies and operational systems using AI recommender–based tools
8. Assessment of equity and diversity in HR decisions and policies
9. Understanding organizational communication structures and dominant values through AI recommender–based models
10. Creating growth and learning pathways tailored to employee characteristics using AI recommender systems
11. AI-driven forward planning for recruitment, retention, and HR development
12. Assessing organizational capacity for continuous learning and innovation through AI recommender–based models

Figure 1

Extracted model including selective and axial codes



In order to identify the factors and components of the AI-based human resource management model using a futures-studies approach, the Delphi method was employed. In this section, the panel consisted of 10 experts. In this study, the perspectives of HR managers in the banking industry in Tehran as well as university faculty members were utilized. A semi-structured interview questionnaire based on the Delphi technique was developed using a 9-point Likert scale. This questionnaire was derived from the literature review and expert interviews conducted in the previous phase of the study, through which the indicators and components of the AI-based HRM model using a futures-studies approach were extracted. The Delphi process was conducted over multiple rounds, and the results are presented below.

For the first round of Delphi, a space was provided at the end of the indicators for each component so that respondents could add additional indicators from their perspective. After designing the first-round questionnaires, the distribution process began. The most significant challenge in accessing respondents was their geographical dispersion. Since most qualitative-phase participants were senior managers, project managers, and university professors in civil engineering and architecture, questionnaires were delivered in person after scheduling appointments at their workplace.

In the first round of Delphi, a series of indicators identified through literature review and expert interviews as factors and components of the AI-based HRM model using a futures-studies approach were included in the Delphi questionnaire. Experts were asked to state their views on these indicators and, if necessary, add any additional indicators they deemed important.

Table 4

Results of the First Round of Delphi

Dimensions	Indicators	Mean	Agreement Coefficient	Decision (Confirm/Remove)
Performance improvement through behavioral data	Team productivity analysis	7.10	0.56	Remove
	Performance evaluation effectiveness analysis	8.00	0.51	Confirm
	AI-based performance analysis	6.98	0.49	Confirm
Learning assessment and effectiveness through educational data	AI-based training-effectiveness evaluation	7.98	0.65	Confirm
	Individual-development analysis in the AI pathway	6.00	0.51	Confirm
	AI-based meeting-effectiveness analysis	6.47	0.54	Confirm
	Employee learning analysis	6.98	0.65	Confirm
Identification of high-risk behaviors and prediction of turnover or reduced motivation	Turnover prediction	6.27	0.77	Confirm
	Turnover-cause analysis	7.96	0.59	Confirm
	Human-resource risk analysis	6.27	0.77	Confirm
	Organizational loyalty analysis	5.60	0.53	Confirm
	Burnout detection	5.64	0.54	Confirm
	Employee-motivation analysis	5.55	0.51	Confirm
Use of algorithms to facilitate and accelerate HR processes	HR-interaction automation	6.00	0.50	Confirm
	Recruitment acceleration	5.81	0.69	Confirm
	Automated data-driven promotion	5.94	0.73	Confirm
	Process optimization with reinforcement learning	5.71	0.56	Confirm
	Intelligent-model-based decision-making	6.10	0.51	Confirm
Insight extraction from behavior, emotions, and interactions	Employee sentiment analysis	7.40	0.73	Confirm
	Ethical-behavior analysis	8.40	0.62	Confirm
	Employee-feedback analysis	7.40	0.72	Confirm
	Real-time employee-satisfaction monitoring	6.40	0.76	Confirm
	Employee-engagement analysis	7.50	0.54	Confirm
Creating growth and learning pathways tailored to employee characteristics	Participation-in-decision-making analysis	6.80	0.55	Confirm
	Personalized career-path design	6.70	0.57	Confirm
	Skill-development pathway recommendation	6.50	0.53	Confirm
	Training recommender system	6.90	0.57	Confirm
	Promotion-path analysis	7.50	0.55	Confirm
	Job-fit analysis	6.70	0.67	Confirm
Understanding communication structures and dominant values	Organizational-culture analysis through data mining	7.50	0.55	Confirm
	Organizational-network analysis	8.40	0.56	Confirm
	Inter-unit interaction analysis	7.30	0.53	Confirm
	Value-alignment analysis	8.50	0.63	Confirm
	Value-fit analysis	6.70	0.66	Confirm
Assessment of equity and diversity in HR decisions	Promotion-equity analysis	7.30	0.68	Confirm
	Resource-distribution justice analysis	8.30	0.66	Confirm
	Diversity-policy effectiveness analysis	8.20	0.64	Confirm
	Organizational-diversity analysis	6.50	0.68	Confirm
	Bias reduction in recruitment	6.80	0.69	Confirm
Measurement of policy and operational system efficiency	HR-policy evaluation	6.70	0.54	Confirm
	Reward-effectiveness analysis	7.70	0.57	Confirm
	Motivation-effectiveness analysis	8.50	0.56	Confirm
	Feedback-effectiveness analysis	7.50	0.53	Confirm
	Communication-effectiveness analysis	7.30	0.54	Confirm

	Process-transparency analysis	6.50	0.71	Confirm
Future-oriented planning for recruitment, retention, and HR development	HR-needs forecasting	8.40	0.84	Confirm
	Data-driven organizational-structure design	8.50	0.63	Confirm
	HR decision-making analysis	6.30	0.65	Confirm
	Key-employee identification	8.30	0.56	Confirm
Assessing capacity for continuous learning and innovation	Organizational-learning analysis	7.20	0.56	Confirm
	Innovation-participation analysis	7.40	0.61	Confirm

The results of evaluating the indicators and components presented to the experts show that the agreement coefficient for all indicators is greater than 0.50, indicating that all factors were approved and none were removed. Additionally, no new indicators or components were added to the model by the experts at this stage.

Since no new indicators or components were added to the model in the first round of the Delphi process, the same indicators and components—along with their scores from the first round—were sent to the experts for reevaluation. They were again asked to evaluate and score the presented indicators and, if necessary, add any additional indicators they deemed important. Table (5) presents the statistical results of the second round of Delphi.

Table 5

Results of the Second Round of Delphi

Dimensions	Indicators	Mean	Agreement Coefficient	Decision (Confirm/Remove)
Performance improvement through behavioral data	Team productivity analysis	7.2	0.63	Remove
	Performance evaluation effectiveness analysis	7.4	0.84	Confirm
	AI-based performance analysis	7.0	0.66	Confirm
Learning assessment and effectiveness through educational data	AI-based training-effectiveness evaluation	7.0	0.59	Confirm
	Individual-development analysis in the AI pathway	6.0	0.64	Confirm
	AI-based meeting-effectiveness analysis	6.0	0.58	Confirm
	Employee learning analysis	7.0	0.67	Confirm
Identification of high-risk behaviors and prediction of turnover or reduced motivation	Turnover prediction	6.0	0.72	Confirm
	Turnover-cause analysis	6.47	0.87	Confirm
	Human-resource risk analysis	7.49	0.88	Confirm
	Organizational loyalty analysis	6.35	0.84	Confirm
	Burnout detection	7.40	0.84	Confirm
	Employee-motivation analysis	7.17	0.73	Confirm
Use of algorithms to facilitate and accelerate HR processes	HR-interaction automation	6.21	0.74	Confirm
	Recruitment acceleration	8.0	0.70	Confirm
	Automated data-driven promotion	6.11	0.71	Confirm
	Process optimization with reinforcement learning	8.0	0.70	Confirm
	Intelligent-model-based decision-making	7.3	0.80	Confirm
Extracting insights from behavior, emotions, and interactions	Employee sentiment analysis	7.21	0.73	Confirm
	Ethical-behavior analysis	8.39	0.84	Confirm
	Employee-feedback analysis	6.04	0.71	Confirm
	Real-time employee-satisfaction monitoring	7.40	0.84	Confirm
	Employee-engagement analysis	6.18	0.73	Confirm
Creating growth and learning pathways tailored to employee characteristics	Participation-in-decision-making analysis	6.0	0.70	Confirm
	Personalized career-path design	6.3	0.81	Confirm
	Skill-development pathway recommendation	6.32	0.82	Confirm
	Training recommender system	7.13	0.72	Confirm
	Promotion-path analysis	7.17	0.73	Confirm
	Job-fit analysis	7.0	0.90	Confirm

Understanding communication structures and dominant values	Organizational-culture analysis using data mining	5.54	0.88	Confirm
	Organizational-network analysis	5.59	0.89	Confirm
	Inter-unit interaction analysis	5.11	0.71	Confirm
	Value-alignment analysis	7.0	0.70	Confirm
	Value-fit analysis	5.17	0.73	Confirm
Evaluation of equity and diversity in HR decisions	Promotion-equity analysis	6.21	0.74	Confirm
	Resource-distribution justice analysis	6.34	0.83	Confirm
	Diversity-policy effectiveness analysis	7.3	0.80	Confirm
	Organizational-diversity analysis	8.21	0.74	Confirm
	Bias reduction in recruitment	8.43	0.87	Confirm
Assessing efficiency of HR policies and operational systems	HR-policy evaluation	5.19	0.74	Confirm
	Reward-effectiveness analysis	5.84	0.66	Confirm
	Motivation-effectiveness analysis	8.5	0.56	Confirm
	Feedback-effectiveness analysis	7.5	0.53	Confirm
	Communication-effectiveness analysis	7.3	0.54	Confirm
	Process-transparency analysis	6.5	0.71	Confirm
Future-oriented planning for recruitment, retention, and HR development	HR-needs forecasting	8.4	0.84	Confirm
	Data-driven organizational-structure design	8.5	0.63	Confirm
	HR decision-making analysis	6.3	0.65	Confirm
	Key-employee identification	8.3	0.56	Confirm
Assessing capacity for continuous learning and innovation	Organizational-learning analysis	7.2	0.56	Confirm
	Innovation-participation analysis	7.4	0.61	Confirm

The results of the second round show that all indicators were confirmed, and none were removed from the analysis. To reach theoretical saturation and ensure the approval of the components and indicators extracted from the second round of Delphi, the agreement coefficient was re-examined using the scores given to the indicators in the second round. If collective agreement was achieved, the Delphi process would end. The results of the second-round Delphi analysis show that all indicators were confirmed and collective agreement was reached. Therefore, the Delphi process was stopped, and the extracted indicators were entered into the quantitative validation phase, the results of which are presented in the next section.

According to the results of Table (6), since the value obtained for the Kendall test statistic in the second stage (0.819) is significant at $\alpha = 0.01$ (sig < 0.01), it is inferred that there is a significant agreement among respondents, and the value of Kendall's coefficient (0.819) indicates a very high level of consensus among participants.

The results of data analysis at this stage led to the extraction of an appropriate model for AI-based human resource management. The extracted model includes 5 main dimensions, 12 core categories, and 51 subcategories or indicators. The final model of the study is shown in Figure (4).

In the next section, the structural model is examined and validated using MICMAC software. The results show that the variable "optimization of processes and policies using intelligent algorithms and models" has the highest influence. The variable "optimization of communication structures and establishment of organizational justice" ranks second in influence. Finally, the variables "assessment and prediction of employee motivation and behavior" rank third, "future-oriented planning for organizational learning, growth, and innovation" rank fourth, and "performance evaluation and improvement through e-learning" rank fifth in their impact on the AI-based HRM model.

Figure 2

Proposed AI-Based Human Resource Management Model

Discussion and Conclusion

The purpose of this study was to design and validate a comprehensive AI-based human resource management (HRM) model using futures-studies techniques, thematic analysis, and Delphi consensus among experts. The results ultimately revealed a five-dimensional model consisting of performance evaluation and improvement through AI, prediction of employee motivation and behavior, optimization of processes and policies using intelligent algorithms, enhancement of communication structures and organizational justice, and future-oriented planning for learning, growth, and innovation. These findings offer several theoretical and practical implications that align with, extend, and in some cases challenge the existing body of literature on AI-driven HRM.

The first major result concerns the centrality of process optimization through intelligent algorithms, which emerged as the most influential dimension within the MICMAC structural analysis. This aligns with the growing recognition that AI's primary contribution to HRM lies in its ability to automate complex decision-making, reduce administrative burden, and enhance speed and accuracy in HR operations [5, 24]. This result is consistent with arguments that algorithmic augmentation transforms recruitment, performance appraisal, and workforce planning by introducing precision and objectivity into HR processes [2, 25]. Prior research similarly notes that AI capabilities strengthen organizational intelligence and support more efficient resource allocation across the employee lifecycle [13, 28]. Thus, the empirical dominance of this construct in our results reinforces global scholarly consensus that process automation and algorithmic enhancement form the backbone of AI-driven HR transformation.

The second dimension—optimization of communication structures and creation of organizational justice—ranked as the next most influential component. This finding suggests that AI is not only a technical enabler but also a socio-organizational catalyst capable of improving transparency, equity, and internal communication. Research demonstrates that AI-supported analytics can reveal hidden patterns of bias, enable fairer promotion and compensation decisions, and improve organizational climate through data-driven interventions [11, 12]. Studies in strategic HRM further highlight that justice and communication serve as key mediators in employee engagement and performance [8, 32]. The current findings extend this literature by showing that AI recommender systems strengthen justice perception through continuous monitoring of fairness indicators and by providing managers with standardized and transparent insights. The alignment between empirical findings and existing scholarship indicates that AI's impact on communication systems has been underestimated historically but is emerging as a critical variable in modern HRM.

A further key dimension—assessment and prediction of employee motivation and behavior—ranked third in influence within the proposed model. The importance of predictive analytics for understanding employee needs, identifying at-risk talent, and detecting burnout reflects the increasing adoption of algorithmic systems for retention management and organizational well-being [6, 16]. Prior research highlights that predictive HRM tools enhance organizational resilience by forecasting turnover risks and enabling early interventions [2, 19]. The results of the current study reinforce the argument that understanding employee behavior requires real-time, data-driven analysis, which AI can provide more reliably than traditional HR systems. They also align with evidence that AI-supported motivational assessment can improve job-person fit and strengthen long-term organizational commitment [12, 27]. The strong ranking of this dimension in the model underscores its importance as a foundational component of future HRM systems.

The fourth dimension—future-oriented AI planning for learning, growth, and innovation—shows that AI enables HRM functions to transcend administrative boundaries and become strategic partners in organizational development. Scholars argue that AI-driven foresight tools improve the capacity of HR departments to anticipate future skills, design adaptive learning pathways, and build innovative organizational cultures [10, 29]. This aligns with global transformations in HR ecosystems, where AI supports predictive workforce analytics and scenario-based planning to prepare organizations for technological turbulence and labor market disruption [14, 31]. The current study expands this literature by demonstrating that AI-enabled learning and development ecosystems are not supplementary features but core pillars of strategic HRM. The finding also echoes previous evidence that innovative and future-oriented HR practices significantly enhance organizational adaptability and resilience [20, 21].

The final dimension—performance evaluation and improvement through e-learning—ranked fifth in influence but remains conceptually foundational. Traditional performance management systems have long been critiqued for subjectivity, administrative complexity, and limited developmental impact. AI-enhanced systems address these weaknesses by offering continuous, data-driven assessments and by linking individual performance directly to personalized development plans [5, 24]. Research also shows that e-learning systems powered by AI enhance engagement, improve knowledge retention, and provide employees with targeted learning content aligned with performance gaps [16, 29]. Our findings confirm that the integration of performance analytics and e-learning constitutes a dynamic, mutually reinforcing system that strengthens employee capabilities and organizational effectiveness.

Collectively, the results of this study provide robust empirical support for a multi-dimensional, interconnected AI-driven HRM model. The five dimensions align with contemporary scholarship indicating that AI has both operational and strategic value in HRM, enhancing efficiency, equity, organizational foresight, and employee development [6, 7, 26]. In addition, the predictive and justice-enhancing capabilities of AI identified in this study echo global HRM trends toward sustainable, ethical, and evidence-based workforce governance [9, 23]. The integration of thematic analysis, Delphi consensus, and MICMAC modeling also contributes methodological value to the field by demonstrating a structured approach to conceptualizing complex AI-HRM interactions. The convergence between our findings and existing literature strengthens the credibility of the proposed model and highlights its relevance in guiding strategic HRM transformations across diverse organizational contexts.

This study, although comprehensive, is limited by its reliance on expert judgment within a specific regional and sectoral context, which may restrict the generalizability of findings. The Delphi panel size, while methodologically acceptable, may not fully capture the diversity of perspectives found in larger organizational ecosystems. Additionally, the model focuses primarily on strategic-level AI applications and does not incorporate implementation-related barriers such as infrastructural constraints, digital literacy, or employee resistance. The cross-sectional nature of data collection also limits the ability to capture evolving AI trends or long-term behavioral effects. Finally, the study relies on qualitative and semi-quantitative approaches, and future statistical validation may strengthen the robustness of model components.

Future research should expand the model across different sectors and cultural environments to enhance generalizability. Longitudinal studies would help examine how AI-driven HRM systems evolve over time and how employees adapt to algorithmic management. Quantitative validation with larger samples could strengthen model reliability and allow for structural equation modeling of causal relationships among the identified dimensions. Further exploration of ethical, psychological, and socio-cultural implications of AI in HRM would enrich understanding of employee acceptance and trust. Finally, comparative international studies may reveal how regulatory, technological, and cultural factors shape the adoption and effectiveness of AI-based HRM models.

Organizations implementing AI-driven HRM should prioritize transparent communication regarding AI functions to foster trust and minimize resistance. HR leaders should invest in upskilling initiatives to enhance digital literacy across the workforce and ensure employees can effectively interact with AI systems. Policies promoting fairness, accountability, and ethical AI use should be institutionalized to avoid unintended bias. Managers should adopt a gradual, phased implementation approach, integrating AI tools in ways that align with existing organizational culture and strategic goals. Finally, organizations should continuously monitor AI-HRM outcomes and adjust systems based on feedback, performance data, and evolving workforce needs.

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Authors' Contributions

All authors equally contributed to this study.

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. Written consent was obtained from all participants in the study.

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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