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Seyed Hamed. Tafteh[1], Ali. Farhadi Mahalli[1*], Ali Reza. Matoufi[1]

1 Department of Public Administration, Go.C., Islamic Azad University, Gorgan, Iran

Corresponding author email address:
alifarhadi@iau.ac.ir

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Presenting a Qualitative Model of Artificial Intelligence Value Creation in the Human Resource Policy-Making Process of the Ministry of Petroleum

ABSTRACT

Digital transformation and the expanding application of artificial intelligence have subjected human resource policy-making processes to fundamental changes and have increasingly highlighted the necessity of reconsidering value-creation models. Despite the importance of this issue, due to the absence of an integrated framework, the aim of this study was to present a qualitative model of artificial intelligence value creation in the human resource policy-making process of the Ministry of Petroleum. In terms of purpose, the present study was applied-developmental, and in terms of method, it was qualitative with a meta-synthesis approach. Data were collected through a systematic search of Persian and English studies published in reputable scientific databases from 2015 to 2025. Studies were evaluated in several stages based on inclusion and exclusion criteria, including language, publication time span, thematic relevance, scientific credibility, and access to full text. These stages included removing duplicate studies, screening titles and abstracts, and reviewing full texts. Finally, 38 eligible studies were included in the meta-synthesis stage. Data analysis was conducted using the seven-step method of Sandelowski and Barroso (2007), and Lincoln and Guba's criteria were used to assess the credibility and trustworthiness of the findings. The results of the study led to the presentation of a qualitative model of artificial intelligence value creation in the human resource policy-making process of the Ministry of Petroleum. This model consisted of four main dimensions, namely agenda setting and prioritization, formulation, implementation, and evaluation, and 23 components. The results indicated that artificial intelligence value creation in human resource policy-making requires organizational digital maturity, data governance and management, development of human resource competencies, establishment of technological infrastructure, human–AI synergy, and deployment of a data-driven evaluation system. Overall, the findings of this study show that artificial intelligence value creation in the human resource policy-making process of the Ministry of Petroleum is a multilevel and integrated process that begins with problem identification and is completed through the formulation of intelligent policies, implementation based on technological infrastructure, and data-driven evaluation. This model indicates that value creation through artificial intelligence requires the simultaneous presence of four essential factors: organizational digital maturity, appropriate governance, human capital readiness, and data management.

Keywords: Artificial intelligence value creation, policy-making, human resources

Introduction

The rapid diffusion of artificial intelligence has moved human resource management from a primarily administrative and experience-based function toward a data-intensive, predictive, and strategically embedded system of organizational decision-making. In contemporary organizations, especially large public and semi-public institutions with complex workforce structures, human resource policies are no longer limited to routine issues such as recruitment, training, compensation, and

performance appraisal; rather, they are expected to support organizational agility, evidence-based governance, workforce resilience, strategic capability development, and long-term value creation. This transformation has intensified the need to rethink how human resource policy-making is conceptualized, formulated, implemented, and evaluated in the age of artificial intelligence. The growing body of research on artificial intelligence in human resource management shows that AI technologies can improve the speed, accuracy, personalization, and predictive capacity of HR processes, but their real organizational value depends on how they are integrated into decision structures, governance mechanisms, human capabilities, and policy cycles [1-3].

Artificial intelligence in human resource management refers to the use of intelligent systems, algorithms, machine learning models, natural language processing, expert systems, and data analytics to support or automate HR-related decisions and activities. These technologies can be applied in recruitment and selection, employee retention, workforce planning, learning and development, performance management, compensation, employee engagement, and talent analytics. Early discussions emphasized the capacity of AI to automate repetitive tasks and increase operational efficiency; however, more recent studies have shifted attention toward its strategic role in redesigning HR architecture, supporting evidence-based decision-making, and enabling value co-creation between humans and intelligent systems [4-6]. This shift indicates that AI should not be regarded merely as a technological tool, but as a strategic capability that can reshape the logic of HRM and its contribution to organizational performance.

One of the most important developments in this field is the transition from digital HRM to AI-enabled HRM. Digital HRM is largely concerned with the digitization of HR processes and the use of information systems to improve administrative coordination, while AI-enabled HRM involves predictive modeling, automated decision support, intelligent personalization, and adaptive learning systems. Studies on AI-HRM emphasize that the adoption of artificial intelligence can improve HR service quality, reduce human error, support data-driven decisions, and enhance employee experience, provided that organizations possess appropriate technological infrastructure, data readiness, managerial commitment, and workforce capabilities [7-9]. Therefore, the value of AI in HRM is not generated automatically through the acquisition of technology, but through the alignment of technological capacities with organizational objectives, HR competencies, and policy requirements.

The concept of value creation is central to understanding the strategic relevance of artificial intelligence in HRM. Value creation refers to the process through which organizational resources and capabilities are transformed into meaningful benefits for stakeholders, including employees, managers, the organization, and society. From a strategic management perspective, value propositions become superior when they are designed around stakeholder needs, organizational capabilities, and differentiated benefits [10]. In the context of AI-enabled HRM, value creation may appear in different forms: improved quality of decisions, enhanced employee retention, reduced operational costs, increased fairness and transparency, better workforce planning, personalized learning pathways, and stronger alignment between HR policies and strategic goals. Recent research has shown that artificial intelligence can unlock value in HRM by strengthening retention strategies, improving talent management, and enabling more precise identification of employee needs and organizational risks [11, 12].

Nevertheless, the implementation of AI in HRM also raises substantial concerns. Algorithmic systems may reproduce or amplify bias, create opacity in decision-making, weaken employee trust, increase fears of replacement, and challenge conventional assumptions about managerial responsibility and human judgment. Human resource development professionals may position AI either as a threat or as an augmentation tool, depending on their understanding of its role in

supporting human capabilities rather than replacing them [13]. This issue is particularly important in public-sector and policy-oriented organizations, where decisions must meet not only efficiency criteria but also standards of legitimacy, fairness, accountability, legal compliance, and public trust. Thus, AI value creation in HR policy-making requires ethical governance, algorithmic transparency, human oversight, and organizational mechanisms that preserve dignity and fairness in human–machine interaction.

Another major challenge concerns organizational readiness. The successful deployment of AI-based HRM requires digital maturity, absorptive capacity, innovation strategy, and the ability to redesign business and administrative models in response to technological change. Research on Industry 4.0 shows that organizations differ in their capacity to absorb digital technologies and transform them into strategic value, and this difference is influenced by innovation strategy, structural flexibility, and organizational learning capability [14]. In HRM, this means that organizations need more than technical infrastructure; they need data governance, digital literacy, change management programs, senior management support, and a culture that accepts evidence-based and technology-supported decision-making. Without these foundations, AI tools may remain fragmented, underused, or even counterproductive.

The Fourth Industrial Revolution has intensified these challenges for HR professionals. Studies indicate that HR functions are under pressure to adapt to automation, advanced analytics, robotics, and intelligent technologies, while simultaneously redefining the skill sets required of HR professionals and employees [15, 16]. This transformation disrupts traditional HR roles and requires new competencies, including data interpretation, digital ethics, algorithmic literacy, strategic workforce planning, and cross-functional collaboration. Minbaeva argues that HRM is undergoing disruption as data, analytics, and digital technologies reshape the way organizations manage people, make decisions, and generate strategic value [17]. Consequently, AI-enabled HRM must be examined not only at the level of tools and applications but also at the level of capabilities, structures, and policy-making processes.

Policy-making provides an important framework for understanding how AI can create value in HRM. The policy cycle generally includes agenda setting, policy formulation, implementation, and evaluation. In digital governance contexts, policy-makers are expected to adapt to rapid technological change, increasing data availability, and more complex stakeholder expectations. Janssen and Helbig argue that innovation in the policy cycle requires preparedness for new forms of data use, digital transformation, and changing governance arrangements [18]. In the same line, studies on artificial intelligence and public policy show that AI can contribute to problem recognition, policy analysis, scenario modeling, decision support, implementation monitoring, and evaluation. However, the effective use of AI in policy-making depends on institutional capacity, regulatory clarity, data quality, and ethical safeguards [19-21].

In human resource policy-making, artificial intelligence can support the agenda-setting stage by identifying workforce problems, predicting HR crises, detecting skill gaps, analyzing employee sentiment, and revealing strategic mismatches between current and desired workforce conditions. At the formulation stage, AI can support scenario analysis, policy simulation, evidence-based design, stakeholder analysis, and the comparison of alternative HR policy options. During implementation, AI can facilitate adaptive guidelines, real-time feedback systems, personalized training, intelligent recruitment, and continuous monitoring of implementation barriers. In the evaluation stage, AI can enable data-driven performance measurement, dashboard-based monitoring, return-on-investment analysis, and comparison between

traditional and intelligent HR policies. These capacities indicate that AI can influence the entire HR policy cycle, but its value depends on integration across stages rather than isolated technological adoption [12, 22].

The literature also emphasizes the importance of human–AI collaboration in HRM. AI systems can process large datasets, identify patterns, and generate predictions more rapidly than human decision-makers; however, human experts remain essential for contextual interpretation, ethical judgment, strategic reasoning, and legitimacy. Therefore, the most productive model of AI use in HRM is not full replacement of human decision-making, but augmentation and co-creation. Value co-creation in AI-driven HRM depends on interactions among technological capabilities, organizational actors, employee acceptance, and governance structures [22]. This perspective is particularly relevant for HR policy-making because policy decisions affect employees' rights, career paths, compensation, learning opportunities, and occupational well-being. Accordingly, AI should be embedded in a framework that combines data-driven analytics with human expertise, managerial accountability, and ethical oversight.

Employee trust and organizational acceptance are also critical for AI value creation. Even when AI tools are technically accurate, they may fail if employees perceive them as unfair, opaque, threatening, or inconsistent with organizational values. Concerns about surveillance, job insecurity, data privacy, and algorithmic discrimination can undermine acceptance and create resistance to implementation. Studies on AI adoption in HRM suggest that organizations must address both technological and social dimensions of implementation, including communication, training, participation, ethical standards, and employee involvement in change processes [7, 13]. Therefore, the implementation of AI in HR policy-making should be accompanied by trust-building mechanisms, clear legal frameworks, transparent data practices, and participatory governance.

Another important dimension is employee retention and talent management. AI can help organizations identify turnover risks, predict employee performance, detect disengagement patterns, and design personalized retention strategies. Machine learning approaches have been applied to employee turnover prediction, demonstrating the potential of data-driven systems to anticipate workforce instability and support preventive HR interventions [23]. Similarly, recent research highlights the role of AI in enhancing employee retention by improving the identification of employee needs, career expectations, and risk factors that influence withdrawal behavior [11]. These applications are highly relevant for large organizations with specialized human capital, where the loss of experienced employees can generate considerable operational and strategic costs.

Despite these opportunities, the existing literature remains fragmented. Some studies focus on AI applications in HR functions, such as recruitment, training, retention, and performance management; others examine AI governance, public policy, data-driven policy analysis, or organizational readiness. Review studies have mapped the opportunities and challenges of AI-HRM, but many of them treat HRM as a set of operational practices rather than as a policy-making process embedded in organizational governance [3, 6, 16]. Likewise, public policy studies examine AI in the policy cycle, but they often do not specify how AI can create value in the specialized domain of human resource policy-making [19, 21]. This fragmentation creates a theoretical and practical gap: there is still a need for an integrated model that explains how AI value creation unfolds across the stages of HR policy-making.

This gap is especially important in strategic and infrastructure-intensive organizations such as the Ministry of Petroleum. Such organizations operate with large, heterogeneous, and highly specialized workforces and must manage human resources in relation to technological change, regulatory requirements, operational continuity, safety, knowledge transfer, and strategic

national priorities. In these settings, HR policy-making requires accurate workforce data, predictive capacity, ethical governance, and alignment between human capital and long-term organizational goals. AI can potentially strengthen this process, but only if its applications are organized within a coherent framework that connects agenda setting, formulation, implementation, and evaluation. The absence of such a framework may result in fragmented digital initiatives, weak integration between HR and technology units, limited trust among employees, and insufficient evidence for evaluating policy outcomes.

Recent discussions on modern HRM also emphasize the need to bridge the gap between research and practice. Paauwe and Van De Voorde argue that contemporary HRM must move beyond abstract theorization and offer actionable insights for organizations facing complex managerial and technological challenges [24]. This argument is directly relevant to AI-enabled HR policy-making, because organizations need models that are not only conceptually sound but also practically applicable. A qualitative meta-synthesis can contribute to this need by integrating dispersed findings, identifying recurring components, and developing a comprehensive model grounded in existing research. Such an approach is appropriate when a field contains diverse but complementary studies and requires conceptual consolidation.

Therefore, by synthesizing the literature on artificial intelligence, human resource management, public policy-making, organizational readiness, value creation, and digital transformation, it becomes possible to identify the core dimensions through which AI creates value in HR policy-making. These dimensions include intelligent problem recognition, strategic workforce foresight, data-driven decision-making, AI governance, ethical and legal regulation, human–AI synergy, implementation readiness, digital infrastructure, employee acceptance, intelligent talent management, personalized HR services, and data-driven evaluation. Together, these elements show that AI value creation is not a single technological intervention but a multidimensional and staged process that requires coordination among technology, human capital, data governance, organizational strategy, and policy legitimacy.

The aim of this study was to present a qualitative model of artificial intelligence value creation in the human resource policy-making process of the Ministry of Petroleum.

Methodology

The present study was applied-developmental in nature and was conducted using a qualitative meta-synthesis approach in terms of data collection method. The purpose of this study was to identify, synthesize, and systematically interpret the findings of previous studies on artificial intelligence value creation in the human resource policy-making process and to present a comprehensive conceptual model. Accordingly, Sandelowski and Barroso's (2007) seven-step method was used as the operational framework for the meta-synthesis. The statistical population of the study included all domestic and international scientific texts related to the topic, which were searched in reputable domestic and international databases. The international databases included ScienceDirect, Emerald, Scopus, ResearchGate, and Google Scholar, while the domestic databases included the Iranian Research Institute for Information Science and Technology, Magiran, NoorMags, the Scientific Information Database of ACECR, and the National Library of Iran. The search strategy was designed based on a systematic combination of Persian and English keywords related to the research topic. The main keywords included "artificial intelligence," "human resource management," "policy-making," "public governance," "value creation," "Artificial Intelligence," "Human Resource Management," and "Policy Making," which were used in various combinations through the

Boolean operators AND and OR. To increase the comprehensiveness of the search, in addition to structured searching, free searching was also conducted in titles, abstracts, and keywords. The time span of the studies was set from 2015 to 2025 in order to cover the latest scientific trends in the field of artificial intelligence and human resource management.

In the study selection process, 126 articles were initially extracted from different databases. After removing duplicates and conducting initial screening based on title and abstract, 64 articles remained for more detailed review. Subsequently, through full-text review and application of the inclusion and exclusion criteria, 38 eligible articles were finally selected for the final analysis. This process was conducted based on the PRISMA approach to ensure transparency, traceability, and reduction of bias in source selection. The inclusion criteria consisted of scientific-research articles published in reputable domestic and international journals, studies related to artificial intelligence in the fields of human resource management and public policy-making, articles with available full text, and studies published within the specified time span. Conversely, the exclusion criteria included non-scientific articles, sources lacking scientific credibility, duplicate studies, articles unrelated to the research topic, and sources outside the specified time span.

The CASP tool was used to evaluate the quality of the selected studies. The articles were assessed in terms of clarity of purpose, methodological appropriateness, data credibility, coherence of findings, and reliability of results. Only studies that met the minimum quality criteria were included in the analysis stage. In the data analysis stage, Sandelowski and Barroso's seven-step method was also used. Accordingly, the research question was first formulated, relevant texts were then collected, and the required data were extracted. Next, the data were analyzed using open and axial coding, and similar concepts were classified into main categories. Finally, by integrating the findings, the conceptual model of artificial intelligence value creation in the human resource policy-making process was extracted. To increase the credibility and trustworthiness of the findings, Lincoln and Guba's criteria, including credibility, transferability, dependability, and confirmability, were used to ensure that the research findings had coherence, accuracy, and scientific reliability.

Findings and Results

In this study, the indicators extracted from the texts of the selected articles and databases were refined and considered as codes. Subsequently, in order to explain the theoretical framework of the study, these codes were organized into broader categories and introduced as the components of the research. Accordingly, the codes and components were identified, and the results are presented in Table 1.

Table 1

Identified Codes and Components

Codes	Component
Simplification of administrative processes; automation of administrative tasks; optimization of task design; elimination of repetitive and non-creative tasks; use of automation to reduce administrative burden; time saving in human resource processes; increasing the speed and accuracy of human resources in performing tasks; reducing workload in human resources; improving the productivity of human resource management processes; improving the quality of human resource services and processes; saving time and allocating time to more strategic tasks; increasing accuracy and reducing human errors in human resource processes.	Optimization of human resource processes
Optimization of recruitment processes; AI-based job interviews; improving person–job fit using artificial intelligence; AI-based recruitment decisions; screening and interview processes through artificial intelligence; reducing time during recruitment and recruitment-related decision-making; improving attraction and recruitment capabilities through artificial intelligence.	Intelligent recruitment and selection
Unbiased decision-making mechanisms; minimizing biased behavior in decision-making; reducing personal biases in employee performance evaluation; preventing personal judgment; reducing human biases in employee selection processes; reducing cultural differences and deep-rooted prejudices in artificial intelligence systems through ethical frameworks; ensuring equal opportunity regardless of age, gender, and race; ensuring fairness in compensation management; eliminating unfair tools in human resource management; fair and unbiased employee ranking; increasing perceived justice; fairness of automated matching between job applicants and job offers; eliminating systematic biases in human resource decision-making algorithms; preserving human dignity in human–machine interactions; continuous tracking and improvement of employees' physical health and mental well-being; improving occupational health and safety; identifying	Ethical principles and fairness

patterns of employee fraud in performing job tasks; rate of compliance with ethical and legal data standards; privacy-preserving algorithms for human resources.	
Redesigning new workflows; job replacement and human–AI collaboration; simplifying and reshaping human resource management practices; downsizing the workforce management structure; reducing administrative paperwork in human resource management; enabling organizational process reengineering and reorganization; separating human resource systems such as recruitment, performance evaluation, and training; threats to clerical jobs; excessive separation of the human resource unit from other organizational units; creating feedback structures.	AI-based organizational architecture
Effectively, efficiently, and sustainably downsizing bureaucracy; designing structure according to policy objectives; designing transparent implementation processes based on modern technologies; developing effective methods for embedding artificial intelligence in organizational frameworks; transformation in human resource management practices; structural alignment; interaction and coordination structures between implementers and formulators; aligning human resource management with artificial intelligence capabilities; increasing adaptability and responsiveness to change.	AI-based organizational architecture
Improving the quality of decisions in the field of human resources through expert systems; greater effectiveness and efficiency of decisions; increasing decision quality and reducing errors; increasing speed and accuracy in policy formulation and implementation; strengthening human decision-making through artificial intelligence; improving the accuracy of predictive models in human resource decisions; institutionalizing data-driven decision-making in human resources; facilitating informed decision-making by combining data analysis and human judgment; analyzing employee behavior; AI-based sentiment analysis; predicting employee performance in a job based on big data analysis; increasing managers' and employees' satisfaction with data-driven decisions; using AI-based decision support systems.	AI-based decision-making maturity
Personalizing human resource services; personalizing employee learning and development; improving employee experience through intelligent systems; designing individualized learning paths based on characteristics and performance; personalizing educational strategies for individuals; personalizing competency-based career paths; providing human resource services and interventions tailored to employees' individual needs.	Intelligent personalization of services
Legal support for the application of artificial intelligence in human resource policy-making; ensuring compliance with regulations and legal requirements in the application of artificial intelligence; developing and updating legal frameworks related to artificial intelligence; transparency in executive frameworks for using artificial intelligence; agility in policy-making in line with technological developments; ensuring the compliance of human resource processes with legal requirements; developing an artificial intelligence governance framework in human resources; determining legal and governance requirements for the application of artificial intelligence; legal considerations in implementing human resource management; aligning disciplinary policies with applicable laws; alignment with international standards and frameworks; improving digital laws in the country; specifying clear upstream laws in the field of artificial intelligence; formulating laws on intellectual property rights in the field of artificial intelligence; ensuring the use of artificial intelligence in labor relations and protecting labor rights; facilitating access to technology under sanctions.	Governance and regulation of artificial intelligence in human resources
Aligning artificial intelligence initiatives with strategic objectives; freeing capacity for strategic focus; reforming and improving AI-based strategic workforce planning; developing strategies for integrating artificial intelligence and human capital; achieving effective strategic planning in human resources; freeing managers' time and cognitive capacity to focus on strategic activities; enhancing the strategic role and position of human resources in the organization.	Enhancing the strategic role of human resources through artificial intelligence
Improving and accelerating agenda setting; identifying issues and problems based on pattern recognition in the agenda-setting and prioritization stage; understanding the current state of human resource-related affairs; predicting human resource crises; identifying strategic gaps between the current and desired states.	Intelligent problem recognition and agenda setting
Formulating human resource policies aligned with technological changes; designing institutional approaches; determining motivational policies; identifying stakeholders; modeling policy impact scenarios; optimizing the legal and regulatory structure based on artificial intelligence; resolving conflicts of interest.	Policy design and formulation
Legitimizing strategic decisions; persuading policy recipients; algorithmic transparency and accountability; managing bias and fairness in intelligent decisions.	Policy governance and legitimacy
Revising implementation processes in accordance with implementation requirements; dynamism of policy implementation processes; real-time feedback on employee performance; automatic adaptation of guidelines to environmental conditions; implementation feasibility; identifying implementation barriers; developing an implementation roadmap.	Implementation readiness management
Predicting and visualizing the consequences of human resource policies; analyzing and designing future scenarios in human resource management; applying predictive analytics in human resource decisions; strengthening a future-oriented approach in human resource management; supporting future-oriented planning and evaluation; changing and enhancing the performance outlook of human resources through artificial intelligence; the role of artificial intelligence in shaping the future outlook of human resources.	Human resource management foresight
Satisfaction with compensation; continuous optimization of rewarding systems through intelligent rewards; aligning the compensation system with desired performance; creating a data-based reward and punishment system; applying artificial intelligence technology in rewards and benefits; increasing fair salaries and rewards.	Intelligent compensation management
Building employee trust in artificial intelligence systems; trust in the results and outputs of artificial intelligence; responding to employees' concerns and ambiguities about artificial intelligence; aligning artificial intelligence initiatives with organizational culture and values; developing a culture of human–AI interaction; managing employee resistance to the adoption of artificial intelligence; enhancing organizational readiness to adopt artificial intelligence; improving change management strategies for artificial intelligence deployment; increasing employee interaction and participation in decisions.	Trust-building and organizational acceptance
Implementing data-based personalized training programs; using artificial intelligence tools and coaches in employee training; creating continuous digital learning opportunities; improving the training and development process through artificial intelligence; aligning training programs with organizational strategic objectives; developing employees' digital skills and learning agility; facilitating the training and socialization of new employees through intelligent platforms; strengthening organizational learning through intelligent technologies.	Intelligent human resource training and learning
Analyzing and evaluating employees' skill gaps; identifying competency gaps in accordance with job requirements; reducing knowledge and skill gaps in the organization; assessing employees' digital and technological literacy; monitoring and identifying employees' skill obsolescence; using intelligent tools to identify and monitor skill gaps.	Intelligent management of skill and knowledge gaps
Developing the hardware, software, and data infrastructures required for artificial intelligence; creating stable and efficient communication infrastructures; designing, operating, and maintaining digital infrastructures; providing up-to-date, stable, and reliable infrastructures; infrastructural support for data collection, storage, and processing; prioritizing the development of technological infrastructures in the organization.	Technological and digital infrastructures supporting artificial intelligence
Developing and enhancing employee competencies; identifying and defining emerging skills required by the organization; aligning competencies with organizational strategic objectives; developing employees' distinctive and competitive competencies; specifying the competencies required for each job; enhancing knowledge and specialized skills in the field of artificial intelligence; formulating and updating digital skill standards; redesigning job profiles based on a combination of technical and soft skills; developing competencies for working with artificial intelligence tools; enhancing digital literacy and mastery of information and communication technology.	Transformation of human resource competencies and skills

Formulating and establishing data management policies and frameworks; integrating human resource data from different sources; ensuring appropriate access to data and analytics; enhancing data quality, integrity, and security; developing data-driven infrastructures for decision-making; using data-driven analytics in human resource policy-making; applying artificial intelligence tools and algorithms in data analysis; enhancing transparency in the use of data and algorithms; monitoring and managing data errors and biases.	Data governance and management in human resources
Identifying and attracting talent using artificial intelligence; retaining key organizational talents; reducing turnover among talented employees; developing and nurturing strategic talents; using proactive strategies in talent management; increasing the effectiveness of the human resource system in talent attraction and retention; improving the talent management cycle in the organization.	Intelligent talent management
Recruiting specialists in artificial intelligence and data; training and developing technical specialists in digital human resources; attracting young and technology-oriented employees to the organization; developing specialized skills in data analytics and artificial intelligence; strengthening the organization's specialized capacity in digital human resource management.	Specialization and development of technology-oriented human resources
Integrating AI-based insights with human expertise in policy-making; collaboration between human resource specialists and artificial intelligence specialists in the decision-making process; interdisciplinary participation involving data, human resources, and ethics in policy formulation; joint use of data-driven analytics and human judgment; developing human–AI interaction in the policy-making cycle; improving the quality of decisions through synergy between humans and intelligent systems.	Human–AI synergy in human resource policy-making
Reducing human resource operational costs through artificial intelligence; reducing employee training and development costs; optimizing human resource budget allocation; optimizing the costs of human resource processes; increasing financial productivity in implementing artificial intelligence solutions; estimating and managing investment requirements for artificial intelligence deployment.	Financial management and cost optimization of human resources
Level of digital literacy and technological skills of managers and employees; degree of senior management support and commitment to artificial intelligence implementation; degree of organizational readiness to implement artificial intelligence projects; reducing organizational resistance to intelligent technologies; level of employee acceptance and positive attitude toward artificial intelligence; degree of perceived job security in the digitalization process; existence of formal change management programs in artificial intelligence deployment; level of digital maturity in human resource policy-making.	Organizational digital maturity
Defining and applying key performance indicators for human resource policies; using management dashboards to monitor policies; comparing the performance of intelligent policies with traditional policies; measuring return on investment in the application of artificial intelligence in human resources; evaluating the degree of improvement in policy performance based on data analysis and artificial intelligence; creating a real-time performance-based feedback system for employees; implementing a continuous, unbiased, and fact-based feedback system; speed of system response to feedback and environmental changes; continuous improvement of policies based on data-driven analysis results.	Data-driven monitoring and evaluation of human resource policies

Table 2 presents the dimensions and components of artificial intelligence value creation in the human resource policy-making process of the Ministry of Petroleum.

Table 2

Dimensions and Components Related to the Study

Dimensions	Components
Agenda setting and prioritization	Intelligent problem recognition and agenda setting; human resource management foresight; AI-based decision-making maturity; enhancing the strategic role of human resources through artificial intelligence; intelligent management of skill and knowledge gaps; organizational digital maturity.
Formulation	Policy design and formulation; governance and regulation of artificial intelligence in human resources; ethical principles and fairness; policy governance and legitimacy; transformation of human resource competencies and skills; AI-based organizational architecture; data governance and management in human resources; human–AI synergy in policy-making.
Implementation	Implementation readiness management; technological and digital infrastructures supporting artificial intelligence; trust-building and organizational acceptance; intelligent recruitment and selection; intelligent talent management; intelligent human resource training and learning; intelligent personalization of services; optimization of human resource processes.
Evaluation	Data-driven monitoring and evaluation of human resource policies; financial management and cost optimization of human resources; specialization and development of technology-oriented human resources; intelligent compensation management.

For artificial intelligence value creation in the human resource policy-making process of the Ministry of Petroleum, 23 components and four dimensions were identified, as presented in Figure 1.

Figure 1

Model of Artificial Intelligence Value Creation in the Human Resource Policy-Making Process of the Ministry of Petroleum

Discussion and Conclusion

The findings of this study led to the identification of a qualitative model of artificial intelligence value creation in the human resource policy-making process of the Ministry of Petroleum. The model consisted of four main dimensions, namely agenda setting and prioritization, formulation, implementation, and evaluation, and 23 components. These findings indicate that the value of artificial intelligence in human resource policy-making is not limited to the automation of human resource functions;

rather, it is created through an integrated policy cycle in which intelligent technologies contribute to problem recognition, evidence-based formulation, adaptive implementation, and data-driven evaluation. This result is consistent with the view that artificial intelligence has moved human resource management beyond administrative digitization toward intelligent decision support, strategic workforce planning, and organizational value creation [1-3]. Accordingly, the findings suggest that artificial intelligence should be understood as a strategic policy-making capability rather than merely as a technical instrument for improving isolated HR operations.

The first dimension of the model was agenda setting and prioritization, which included intelligent problem recognition and agenda setting, human resource management foresight, AI-based decision-making maturity, enhancement of the strategic role of human resources through artificial intelligence, intelligent management of skill and knowledge gaps, and organizational digital maturity. This dimension shows that artificial intelligence can create value at the earliest stage of the policy process by helping organizations identify workforce-related problems before they become critical, detect patterns in employee behavior, anticipate future skill needs, and prioritize HR issues based on evidence. This finding aligns with studies emphasizing that AI can improve policy analysis, support issue identification, and strengthen data-driven agenda setting in public policy-making [19-21]. It also corresponds with the argument that policy cycles are changing under the influence of digital technologies and that policy-makers must be prepared to use data, analytics, and intelligent systems in identifying and framing policy problems [18].

The inclusion of organizational digital maturity in the agenda-setting dimension is particularly important. The results indicate that the ability to recognize and prioritize HR issues intelligently depends on the organization's digital literacy, technological readiness, senior management commitment, and positive attitude toward AI. This finding is consistent with research on Industry 4.0 and digital transformation, which shows that organizations can derive strategic value from new technologies only when they possess absorptive capacity, innovation orientation, and structural readiness [14]. In the HRM context, this means that AI-based value creation begins before implementation; it begins with the organization's capacity to understand data, interpret digital signals, and transform technological potential into strategic policy priorities. This interpretation is also supported by studies showing that HR professionals need new skills and readiness to operate effectively in the Fourth Industrial Revolution [15, 17].

The second dimension of the model was formulation. This dimension included policy design and formulation, governance and regulation of artificial intelligence in human resources, ethical principles and fairness, policy governance and legitimacy, transformation of HR competencies and skills, AI-based organizational architecture, data governance and management in human resources, and human–AI synergy in policy-making. These findings show that the formulation of AI-enabled HR policies requires more than technical design; it requires legal, ethical, institutional, structural, and human-centered arrangements. This result is consistent with studies that regard AI-HRM as a multidimensional field involving opportunities as well as challenges related to bias, accountability, privacy, transparency, legal compliance, and employee trust [7, 8, 16]. Therefore, AI value creation in HR policy formulation depends on the establishment of governance mechanisms that define how AI systems are designed, monitored, explained, and aligned with organizational and social values.

The emergence of ethical principles and fairness as a component of formulation confirms that intelligent HR policy-making cannot be reduced to efficiency. In organizations such as the Ministry of Petroleum, HR policies affect employment opportunities, career development, compensation, evaluation, and occupational security. Therefore, any use of AI must

ensure fairness, equal opportunity, reduction of bias, protection of privacy, and preservation of human dignity. This finding supports previous research warning that AI may reproduce systematic bias if ethical safeguards and governance frameworks are not established [6, 12]. It also reinforces the idea that the strategic value of AI depends on responsible deployment and not simply on algorithmic performance. Thus, the formulation stage must integrate algorithmic transparency, human oversight, legal regulation, and legitimacy-building mechanisms.

Another important result in the formulation dimension was human–AI synergy. The findings suggest that AI value creation is maximized when data-driven insights are combined with human judgment, professional expertise, and contextual understanding. This result is in line with studies that describe AI not merely as a replacement technology but as an augmentation mechanism that can support human decision-making and improve the quality of HR decisions [13, 22]. In HR policy-making, human–AI synergy is especially critical because policy decisions require normative reasoning, organizational sensitivity, and awareness of employee needs. AI may identify trends, simulate scenarios, and generate predictive insights, but human actors must interpret these outputs in relation to organizational strategy, ethical standards, and implementation feasibility.

The third dimension of the model was implementation, which included implementation readiness management, technological and digital infrastructures supporting AI, trust-building and organizational acceptance, intelligent recruitment and selection, intelligent talent management, intelligent HR training and learning, intelligent personalization of services, and optimization of HR processes. These results show that implementation is the stage in which AI value creation becomes operational and visible. The findings are consistent with studies that identify recruitment, talent management, employee training, HR service delivery, and process optimization as major domains of AI application in HRM [3-5]. However, the present findings go further by showing that these applications must be embedded within a broader implementation readiness framework that includes infrastructure, acceptance, trust, and change management.

The identification of intelligent recruitment and selection, talent management, and personalized HR services indicates that AI can create value by improving the fit between individuals, jobs, competencies, and organizational needs. AI can support screening, prediction, matching, and individualized development, thereby improving both efficiency and decision quality. This result is consistent with studies showing that AI can enhance employee retention, identify talent risks, and support proactive HR interventions [11, 23]. In particular, machine learning-based prediction of turnover and performance can help organizations design more targeted policies for talent retention and workforce stability. For the Ministry of Petroleum, where specialized expertise and long-term human capital development are strategically important, these applications can be especially valuable.

The inclusion of trust-building and organizational acceptance in the implementation dimension confirms that technical capacity alone is insufficient for AI-based transformation. Employees may resist AI if they perceive it as threatening, unfair, opaque, or inconsistent with organizational values. Therefore, the successful implementation of AI-enabled HR policies requires communication, participation, training, and assurance regarding privacy, job security, and fairness. This finding aligns with research indicating that HR professionals and employees may experience both fear and opportunity in relation to AI, depending on whether it is framed as replacement or augmentation [13]. It also corresponds with studies emphasizing that AI-HRM adoption requires attention to organizational culture, employee readiness, and change management [7, 9]. Thus, AI value creation is partly technological and partly social.

The fourth dimension of the model was evaluation, which included data-driven monitoring and evaluation of HR policies, financial management and cost optimization of HR, specialization and development of technology-oriented human resources, and intelligent compensation management. This dimension indicates that AI creates value not only by improving policy design and implementation but also by enabling continuous assessment of policy outcomes. Through dashboards, key performance indicators, real-time feedback, return-on-investment analysis, and comparative evaluation of traditional and intelligent policies, organizations can monitor whether AI-enabled HR policies actually improve performance and create sustainable value. This result supports the argument that value creation requires systematic evaluation of benefits, costs, and stakeholder outcomes [10]. It also aligns with studies emphasizing the importance of AI capability frameworks for unlocking value in HRM [12].

The evaluation dimension also highlights the financial and strategic implications of AI in HRM. AI may reduce operational costs, optimize HR budgets, improve compensation decisions, and support evidence-based allocation of resources. However, such benefits require investment in infrastructure, specialized human resources, and continuous evaluation. This interpretation is consistent with studies that emphasize the financial, legal, and skill-related implications of AI-enabled HRM [8, 16]. The presence of specialization and technology-oriented workforce development in the evaluation dimension indicates that the sustainability of AI value creation depends on cultivating professionals who can interpret AI outputs, manage digital HR systems, and connect data analytics with HR policy goals.

Overall, the findings suggest that artificial intelligence value creation in HR policy-making is a systemic and staged process. It begins with the intelligent recognition of problems and strategic priorities, continues through ethical and evidence-based formulation, becomes operational through infrastructure-supported implementation, and is sustained through data-driven evaluation and continuous improvement. This systemic interpretation is consistent with research on value co-creation in AI-driven HRM, which emphasizes the interaction among AI capabilities, organizational actors, data systems, and human expertise [22]. It also supports the broader argument that modern HRM must bridge research and practice by providing models that are conceptually robust and practically applicable [24]. Therefore, the model developed in this study contributes to the literature by integrating AI-HRM, public policy-making, digital governance, and strategic value creation into a coherent framework.

This study had several limitations. First, because the research was conducted using a meta-synthesis approach, the findings depended on the quality, scope, and availability of previous studies. Although quality appraisal was applied, the included studies differed in terms of methodology, context, conceptual depth, and empirical rigor. Second, the model was developed based on available scientific literature and was not empirically tested in the Ministry of Petroleum through quantitative modeling, field observation, or large-scale survey data. Third, although the study focused on the Ministry of Petroleum, some extracted concepts originated from broader HRM, public policy, and AI governance literature, and their direct applicability may vary across departments, occupational groups, and administrative levels. Fourth, the rapidly evolving nature of artificial intelligence means that some technologies, regulations, and implementation challenges may change over time.

Future studies should empirically test the proposed model using quantitative and mixed-method designs in the Ministry of Petroleum and other large public-sector organizations. Researchers can examine the relationships among the four main dimensions, determine the relative importance of each component, and evaluate how organizational digital maturity, data governance, employee trust, and infrastructure readiness influence AI value creation in HR policy-making. Future research

may also develop valid measurement instruments for the identified components and use structural equation modeling, fuzzy Delphi, interpretive structural modeling, or system dynamics to examine causal relationships. Comparative studies across ministries, industries, and countries can also clarify how legal, cultural, technological, and institutional differences shape the adoption and effectiveness of AI-enabled HR policy-making.

Managers and policy-makers in the Ministry of Petroleum should treat artificial intelligence as a strategic governance capability rather than a set of isolated digital tools. Before implementing AI-based HR systems, the organization should assess its digital maturity, data quality, legal readiness, workforce skills, and cultural acceptance. Clear governance frameworks should be established for data management, algorithmic transparency, ethical oversight, privacy protection, and human accountability. HR professionals should be trained in data literacy, AI interpretation, digital ethics, and evidence-based policy-making. The ministry should also design pilot projects in recruitment, training, talent management, compensation, and policy evaluation, and gradually scale successful initiatives based on measurable outcomes, employee feedback, and continuous monitoring.

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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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