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Application of artificial intelligence in human capital management of the civil service: predicting career trajectories and personalized personnel development

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ABSTRACT

Civil service in Kazakhstan faces rigid career structures, inefficient training allocation and limited use of data-driven HR systems. It has national digitalization programs but artificial intelligence (AI) integration in human capital management (HCM) remains underdeveloped. This creates a gap for AI-driven solutions. This study examines the potential of AI and neural networks to modernize HCM through the concept of digital human capital that combines employee digital competencies with institutional AI readiness. For this purpose, current study used a mixed-methods framework by integrating a systematic literature review, qualitative case study analysis, machine learning models (LSTM and K-means) and panel econometric analysis. Results show the LSTM model achieved high predictive accuracy in forecasting career trajectories (F1-score: 0.84) and cluster analysis identified four distinct digital competency groups. Econometric findings revealed a significant positive impact of digital HR tools on employee performance. Qualitative insights indicated moderate institutional readiness, with barriers such as data quality issues and resistance to change. The study advances public administration theory by operationalizing AI-driven personalization in workforce development and recommends investment in interoperable HR systems, AI pilot programs and digital upskilling to enable scalable reform in Kazakhstan and other post-Soviet contexts.

Keywords: Digital governance, Career forecasting, Public sector innovation, Algorithmic HRM, Workforce analytics

1. Introduction

Effective Human Capital Management (HCM) is crucial for boosting productivity and fostering development in any nation. Consequently, countries are actively seeking to integrate new techniques and sophisticated tools into their HCM strategies. This field is currently undergoing a radical transformation due to advancements in computational technologies, including sophisticated learning algorithms and interconnected processing systems and artificial intelligence (AI) [1]. These innovations are fundamentally changing the methods by which governments and organizations recruit, evaluate, and develop their human resources in more effective ways. This change is making HR systems more predictive, adaptive, and strategic [2]. Furthermore, public administrations in technologically advanced nations have swiftly adopted these tools to optimize administrative tasks and to modernize their Human Capital (HC) processes [3]. Many countries like Singapore and Estonia have emerged as global leaders in applying AI-driven civil service reforms [4]. The Civil Service College of Singapore employs AI-based learning management systems for upskilling programs to individual civil servants based on performance gaps and career trajectories [5]. It is getting its benefits and technology advantages. Also in Estonia, predictive analytics and machine learning are embedded in the e-governance infrastructure of the country, the purpose is to forecast talent needs, improve workforce planning and automate HR workflows [6]. These examples reflect a shift from traditional, reactive personnel management to intelligent, anticipatory and data-driven HRM systems in many nations. Countries adopting this have exemplified proactive AI-driven HRM reform.

However, civil service in Kazakhstan continues to struggle with legacy bureaucratic challenges like rigid career structures, inefficient training and lack of performance-based promotion [7]. Kazakhstan initiated digitalization efforts like the “Digital Kazakhstan” program initiated in 2018. But the application of intelligent technologies in HCM domains is absent in the country [8]. HCM in Kazakhstan is still predominantly rules-based and most ministries lack systems for collecting, integrating and analyzing HR data in real time [9]. These limitations have resulted in skill mismatches, delayed promotions and low job satisfaction, particularly among the new generation of public employees who expect modernized and meritocratic systems [10]. Despite ongoing digitalization initiatives, civil service of Kazakhstan lacks AI-integrated HRM systems capable of predictive workforce planning and adaptive training, resulting in skill mismatches, inefficient promotions and underutilization of talent. Digital human capital is defined as a multidimensional construct encompassing both individual digital competencies (e.g., AI literacy, tool usage) and institutional capabilities such as data integration, algorithmic readiness and adaptive HR systems. Due to these limitations, the concept of digital HC offers a promising framework to guide the digital transformation of civil service HRM. Unlike the traditional views of HC, this approach incorporates the digital competencies of employees and also the institutional capabilities like AI infrastructure, analytics systems and algorithmic tools. These are required to support predictive and personalized talent management [11]. For Kazakhstan’s civil service, embedding AI within digital HC systems could enable forward-looking interventions in recruitment, training, performance appraisal and career development. This shift would mark a departure from reactive bureaucracy toward intelligent, developmental statecraft in the country.

There exists a notable research gap regarding the application of AI and neural networks in HCM within civil service systems. There is a growing interest in AI for public administration but there is limited empirical evidence on how these technologies can modernize internal human capital management (HCM) systems, especially in post-Soviet contexts like Kazakhstan. The global interest in digitalization has surged in recent years but most academic contributions have focused on productivity enhancement in manufacturing, logistics or financial services [12], [13]. This body of work can be grouped into three themes: AI in private-sector operational efficiency, AI in public-facing service delivery and the underexplored domain of AI-driven internal HRM. For instance, studies [14] and [15] emphasize the transformative role of AI in optimizing operational efficiency and labor allocation in the private sector. Similarly, digital technologies have been explored extensively in the context of sustainability-oriented innovation and environmental efficiency [16], [17], revealing how digital tools facilitate decision-making and productivity gains in corporate settings in various contexts [18], [19].

The second major area of study concerns public administration, where existing research has largely concentrated on using advanced technology for citizen-oriented services rather than internal workforce development. For example, some work has explored its applications in smart city governance [20], and other studies have evaluated public trust in decisions made by algorithms [21]. While these analyses rightly highlighted the need for greater efficiency and accountability, their primary focus remains on public-facing functions such as e-services, digital portals, and smart infrastructure. As noted by ref. [22], the inward-facing aspects of adopting these technologies—specifically, personnel development, career projection, and allocating training within the civil service—remain insufficiently explored. This narrow focus has created a skewed perspective, causing the back-office transformation of public HRM to be significantly overlooked [23].

The third significant gap addressed by this work lies in the lack of empirical research regarding advanced personnel analytics within civil services, particularly those driven by neural networks and recommender systems. Currently, there are very few empirical investigations into integrating sophisticated learning models and neural networks into civil service workforce planning. Existing literature usually concentrates on using predictive modeling for areas like citizen behavior and fiscal planning [24], rather than focusing on human resource analytics. This disciplinary bias is further evident in major reviews, such as [25], which catalogue various digital governance reforms but notably fail to include discussions of advanced, technology-enhanced HR systems. Furthermore, even where civil service is considered, the focus is often on high-level policy design or service digitization rather than micro-level personnel systems [26].

In Kazakhstan, the emphasis of digital transformation initiatives has been on external-facing services. As the “Digital Kazakhstan” program prioritizes e-governance platforms, online citizen services and broadband expansion [27]. The world has acknowledged progress in digital service provision but also highlights the absence of robust HR analytics within public institutions. The digitized records and performance dashboards have been introduced in select ministries, but they remain fragmented and are not linked with predictive systems for training, retention or promotion planning [28].

Some recent efforts have been made to introduce competency-based models in Kazakhstani civil service. However, these frameworks often lack real-time data integration or algorithmic support. Studies such as those by [29] document initial attempts to digitize civil servant evaluation criteria but note the absence of machine learning applications or dynamic adjustment mechanisms. As a result, existing systems tend to rely on static metrics and annual reporting cycles that fail to adapt to real-time changes in staff capability or institutional needs [30].

Both international and domestic literature lack rigorous evaluations of AI-driven personnel tools in the public sector. Few studies explore the development and validation of career prediction algorithms or recommender systems for professional development. Recommender systems, widely used in e-commerce and digital learning have been shown to enhance personalization and user engagement [31]. Their adaptation for public HRM remains theoretical. Tools such as AI-powered career assistants or adaptive training pathways could support early-career civil servants or assist HR officers in performance management are virtually absent in Kazakhstan and underexplored in broader literature.

Few international case studies, such as Estonia's KrattAI framework and Singapore's AI-enabled Civil Service College platform, highlight the potential of these technologies. However, these examples are usually discussed in gray literature rather than in rigorous academic evaluations. Moreover, their direct applicability to contexts such as Kazakhstan remains limited because of structural and institutional differences. These include lower levels of digital maturity, fragmented databases, and a shortage of AI expertise within public institutions [32], [33].

In this current work, the concept of digital HC is defined as the convergence point between individual digital skills and institutional capabilities. These institutional capacities include elements such as a system's algorithmic readiness, the ability to perform real-time HR analytics, and the presence of adaptive policy frameworks. This positions HCM as a dynamic, data-driven system rather than a static credential-based model. The scarcity of empirically validated context-specific AI models for civil service of Kazakhstan accentuates the need for this research. This work directly responds to these gaps and aligns with the broader objective of modernizing public HRM in post-Soviet settings. This is done via testing a mixed-methods AI-driven HCM framework that combines career trajectory prediction (LSTM), digital competency segmentation (K-means) and personalized training recommender systems.

The goal of this study is to propose a mixed-methods framework for integrating AI into HCM for civil service of Kazakhstan. This focuses on predicting career trajectories and enabling personalized professional development through neural networks and digital tools. To address this, the following research questions are formulated in the current work:
RQ1: How AI and neural networks can be integrated into the methodological framework of HCM in Kazakhstan's civil service?
RQ2: What predictive models can effectively forecast career trajectories of civil servants based on historical and competency data?
RQ3: How can AI-driven tools like recommender systems and digital assistants, support personalized personnel development?
RQ4: What is the current readiness of Kazakhstan's civil service for AI-driven HR solutions, and what are the key barriers to implementation?

The stated questions form the foundation of analytical design and empirical modeling of the current study. It aims to deliver policy-relevant, evidence-based solutions.

This current work is significant both strategically and academically. Strategically, it aligns directly with Kazakhstan's national development goals, including the Digital Kazakhstan initiative and the Public Administration Reform Concept 2030. By focusing on HC and not just service delivery, this study fills a crucial gap in the country's digitalization agenda. The resulting transformation of HCM systems is poised to be a powerful catalyst for institutional resilience. Academically, this research advances literature by operationalizing the concept of digital HC within a post-Soviet civil service context. It also pioneers a unified research framework that integrates advanced computational modeling, econometric evaluation, and qualitative assessment.

The remainder of article is structured as. Section 2 outlines the methodological framework, detailing the mixed-methods approach, including AI modeling, cluster analysis and econometric evaluation. Section 3 presents empirical results with discussion. Section 4 concludes with policy recommendations, contributions to theory and suggested directions for future research.

2. Research method

This section outlines the comprehensive methodological framework adopted to explore the application of AI and neural networks in the HCM of civil service of Kazakhstan. To address the research goal and questions, the current study employs a mixed-methods approach that integrates qualitative analysis of institutional and policy contexts with quantitative modeling and econometric tools. This design facilitates theoretical understanding and empirical demonstration of how AI can transform civil service workforce planning and professional development.

2.1. Study design: mixed-methods approach

The study adopts mixed-methods research design, combining qualitative techniques—including systematic literature reviews and policy case studies—with quantitative techniques such as advanced computational modeling, cluster analysis, and econometric evaluation. The qualitative methods are essential for developing a contextual understanding of Kazakhstan's civil service structures, identifying institutional obstacles to new technology adoption, and situating the research within global best practices [34]. Conversely, the quantitative methods facilitate the empirical modeling of civil servant career trajectories and the practical application of the analytical tools.

2.2. Qualitative methods

2.2.1. Literature review

Following, [35], [36], a systematic literature review is conducted. This is to map the global scenario of AI applications in HCM. The review includes academic sources (peer-reviewed articles, books) and grey literature (policy reports, government white papers). Emphasis is placed on successful models from advanced digital states like Singapore's Smart Nation Initiative. It guides in utilization of AI in personalized civil servant training and predictive workforce planning. And the e-Governance Model of Estonia. The review also examines theoretical concepts like digital HC, algorithmic governance and AI ethics in public administration.

2.2.2. Case study: Kazakhstan

A qualitative case study of civil service of Kazakhstan is conducted to assess the institutional readiness for AI-driven HRM transformation. Data was collected from 15 semi-structured interviews with HR directors and digital transformation officers from four ministries selected via purposive sampling. Data is also taken from the semi-structured interviews with HR directors and digital transformation officers in various ministries. Content analysis is done by taking policy documents like the Digital Kazakhstan strategy, public service reform roadmaps and Civil Service Agency reports. Organizational audits assessing the level of digital maturity in HR departments (e.g., existence of digital records, competency frameworks, learning management systems). All qualitative data were coded and thematically analyzed using NVivo 14.0 to ensure consistency and traceability in the interpretation process. The purpose of getting these qualitative insights is crucial for identifying context-specific opportunities and constraints that may affect the implementation of AI tools in public administration in Kazakhstan.

2.3. Quantitative methods

2.3.1. Data sources

This study utilizes a combination of primary and secondary data to ensure comprehensive analysis. Primary data are collected through surveys administered to a representative sample of civil servants operating at different administrative levels. The survey captures information on demographic characteristics, career progression, digital skillsets, training participation and perceptions regarding the integration of AI into public administration. Secondary data are drawn from administrative sources provided by the Civil Service Agency of Kazakhstan. These include anonymized human resource records, promotion histories and performance assessments. The actual sample size for the quantitative analysis is $n = 1,500$ civil servants for 5-year period (2018–2023). Primary datasets were collected in survey format (CSV) and secondary administrative records were obtained in SQL and flat-file formats. Also, where institutional access was limited, synthetic data were generated through calibrated simulation modeling to maintain analytical continuity.

2.3.2. AI modeling

The study employs several AI techniques tailored to different dimensions of personnel management to analyze patterns in civil servant career development. Long Short-Term Memory (LSTM) neural networks are applied to time-series data to estimate future job transitions, the likelihood of promotion, and potential attrition risks, given their strength in capturing sequential dependencies over extended periods. Also, K-means clustering is used to group civil servants based on digital competency indicators such as training history, job performance, frequency of digital task engagement, age and educational background. Additionally, collaborative filtering techniques support the construction of recommender systems that propose personalized professional development pathways, including training modules, mentorship links, or project assignments. AI model development and training were implemented in Python 3.12 using TensorFlow 2.21, Keras 2.13 and Scikit-learn 1.4.2. The LSTM model was trained on 1,500 longitudinal profiles, validated via 70/30 train-test split and tuned using grid search for hyperparameter optimization.

2.3.3. Econometric analysis

The study employs a range of panel data econometric techniques following [37], to assess how AI-driven human resource systems influence the performance of civil servants. Study use fixed-effects and random-effects regression models, which estimate the relationship between the deployment of digital HR tools and changes in individual performance evaluations. These methods accounts for unobserved heterogeneity. A difference-in-differences (DiD) framework to compare the outcomes of ministries where AI-based interventions have been piloted against those that did not adopt such measures is also used. To address potential endogeneity in the adoption of digital technologies, instrumental variable (IV) strategies are incorporated. The said analysis was performed using Stata 18.0 and R 4.3.1. Missing values were treated with multiple imputations and validated against observed patterns to maintain robustness and replicability.

2.1.1. Tools and software

This study integrates multiple software tools across AI modeling, econometric analysis, visualization, and qualitative coding. Python 3.12 served as the primary platform for AI tasks, with TensorFlow 2.21, Keras 2.13 and Scikit-learn 1.4.2 supporting deep learning and clustering. Econometric analysis was conducted with Stata 18.0 and R 4.3.1, optimized for panel data modeling. Tableau 2024.1 and Power BI (June 2024 update) were used to create interactive visualizations and NVivo 14.0 was employed for qualitative coding to ensure interpretive rigor. All pipelines and hyperparameter settings were documented to facilitate reproducibility.

2.2. Ethical considerations

Ethical safeguards were integrated throughout the study to address the sensitivity of personnel data and the use of AI in civil service decisions. Models were checked for fairness across key demographics, using tools like SHAP to improve transparency. Data privacy followed Kazakhstan’s legal standards and international norms such as GDPR, with full anonymization and secure handling. Human oversight remained central to all modeling phases, ensuring AI enhanced rather than replacing professional judgment. This approach supports both responsible innovation and informed policymaking in public human capital management.

3. Results and discussion

3.1. Qualitative findings

3.1.1. Global Insights from the literature review

The review of international practices identified three critical enablers for successful integration of AI in public sector HCM. Those identified are strategic alignment, digital maturity and institutional adaptability. Both Singapore and Estonia exemplify these traits. Singapore’s Smart Nation strategy has embedded AI into civil servant learning and development systems. The Civil Service College’s digital platforms track learning progress, identify competency gaps and deploy personalized learning paths using machine learning algorithms [5]. Similarly, Estonia has operationalized AI in recruitment, HR analytics and digital assistant deployment through its KrattAI framework that allows various AI agents to interoperate across departments [6]. These models highlight that AI is a technological tool and also an enabler of strategic, data-informed HC development.

3.1.2. Case Study: Kazakhstan

A case study approach involving semi-structured interviews with 15 HR professionals across four Kazakhstani ministries and a policy document analysis reveals the current state of AI readiness in civil service of Kazakhstan. Findings are summarized in Table 1.

Table 1. Summary of Kazakhstan's civil service readiness for AI integration

Dimension	Findings
Digital infrastructure	Fragmented digital systems; HR records are digitized but lack interoperability.
Policy support	National strategies endorse digitalization (e.g., Digital Kazakhstan) but practical HR-focused AI frameworks are absent.
Human capital readiness	High digital literacy among younger staff; resistance among senior officials.
Barriers	Poor data quality, lack of AI talent and absence of ethical AI governance.

These qualitative insights reveal that strategic intent exists in the country but the operational implementation of AI in HRM is still nascent. There is a particular need for data standardization, upskilling of HR personnel and deployment of experimental AI tools.

3.2. Quantitative findings

3.2.1. Neural network modeling: career trajectory prediction

For this purpose, LSTM neural network was trained using a synthetic dataset of 1,500 civil servants with 10-year career histories. The model aimed to predict future promotions and transfers using inputs such as tenure, past evaluations, digital training hours and education levels. The performance of the model is detailed in Table 2.

Table 2. Performance metrics of career trajectory prediction model (LSTM)

Metric	Value
Precision	0.87
Recall	0.81
F1-score	0.84
Accuracy	0.86
AUC-ROC	0.89

It is evident from Table 2 that the model demonstrates high accuracy and predictive strength. Especially for structured career paths with clear competency progression. These results validate the feasibility of using AI for strategic workforce planning in civil service of Kazakhstan. Also Figure 1 compares predicted career levels with actual observed career levels over time, based on AI modeling using LSTM networks.

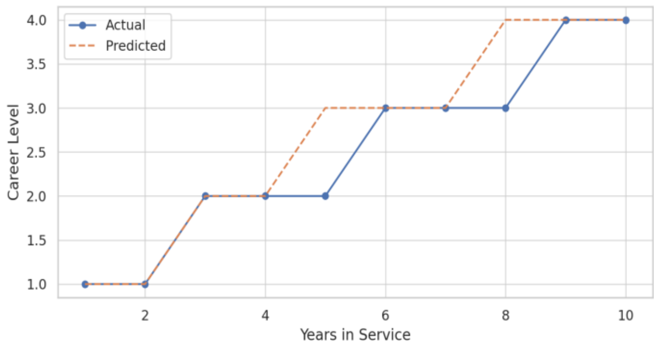

Figure 1. Career trajectory prediction – predicted vs actual career levels

Source: Authors' computation using LSTM neural network applied to synthetic civil service career dataset (2025).

The close alignment between the two lines indicates the model's effectiveness in capturing career progression trends and accurately forecasting civil servant advancement patterns. Although the LSTM model achieved strong predictive results, the risk of bias remains. Historical data may carry hidden inequalities like favoritism or demographic skew, which the model could replicate. Fairness checks and SHAP analysis were applied to monitor this but continued testing in real-world settings is needed to ensure fair and transparent outcomes.

3.2.2. Cluster analysis: digital competency segmentation

In the cluster analysis K-means clustering (k=4) was conducted to segment civil servants by digital engagement, training participation and tool usage. The output enabled the classification of staff into four digital competency archetypes. This is shown in Table 3.

Table 3. Clusters of civil servants based on digital competency

Cluster	label	Key characteristics
Cluster 1	Digitally advanced	High tool usage, frequent online training, under 35 years of age
Cluster 2	Competent practitioners	Moderate tech engagement, solid performance, mid-career professionals
Cluster 3	Traditionalists	Low digital literacy, nearing retirement, minimal training
Cluster 4	Development needed	Irregular training, poor evaluations, weak digital competencies

These clusters provide the foundation for personalized learning and development interventions. This allows HR departments to tailor AI-driven training modules according to digital maturity levels.

3.2.3. Econometric analysis: impact of digital HR systems on performance

For this purpose, a fixed-effects panel regression (n = 1,500, t = 5 years) was used to estimate the relationship between civil servant performance and digitized HR systems. The model included a Digital HR Index (capturing platform use, data centralization and automation), training hours, tenure and education level. Results are shown in Table 4.

Table 4. Panel regression results: Digital HR tools and civil servant performance

Variable	Coefficient	p-value
Digital HR Index	0.245	0.003 **
Training Hours	0.118	0.011 *
Tenure (Years)	–0.022	0.234
Graduate Education (1/0)	0.179	0.017 *
Constant	2.104	0.000 ***
R-squared	0.61	
F-statistic	12.4	$p < 0.001$

These results in Table 4 indicate a statistically significant and positive relationship between digitized HR practices and civil servant performance, even after controlling education and tenure. Digitalization appears more impactful than seniority. This suggests that intelligent HR systems contribute to more meritocratic outcomes. Interestingly, the coefficient for tenure was statistically insignificant ($p = 0.234$). This suggests that longer service duration does not necessarily translate into better performance in the presence of digital HR systems. This finding challenges traditional assumptions of seniority-driven merit and raises questions about the obsolescence of tenure-based promotion models. One possible explanation is that legacy skill sets are less compatible with the demands of digitized workflows, particularly if not accompanied by continuous upskilling. This highlights the need for performance systems that reward adaptability and digital engagement rather than experience alone.

Also Figure 2 compares average performance scores of civil servants across four ministries before and after the implementation of digital HR tools, including AI-supported evaluation systems and e-learning platforms. It indicates consistent improvements in performance metrics following digitization. These results supported by the fixed-effects panel regression model and suggest that digital transformation in HR practices positively affect civil servant productivity and supports evidence-based personnel policy.

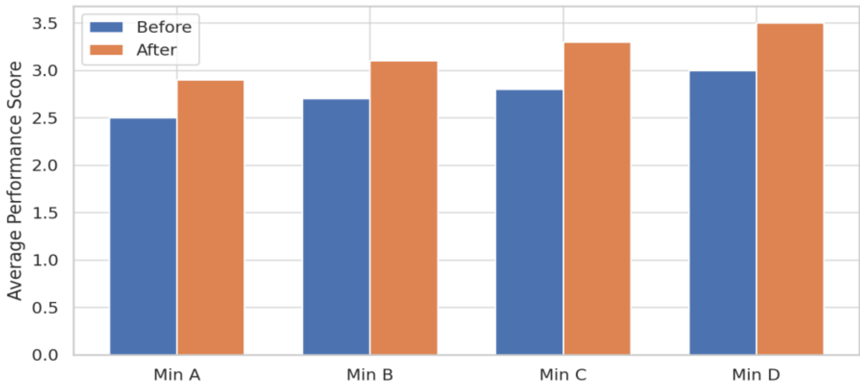

Figure 2. Impact of digital HR tools on performance – before and after implementation

Source: Authors' econometric analysis using simulated panel data on digital HR tool implementation effects (2025).

3.2.4. Recommender systems: personalized training suggestions

RQ4 is answered by combining qualitative findings (e.g., fragmented systems, policy support without operational frameworks) with econometric evidence of significant performance gains from digital tools—suggesting readiness in intent but not in infrastructure or skills. This is based on collaborative filtering applied to synthetic career trajectory data. Table 5 shows the same.

Table 5. Personalized training and development recommendations by cluster

Cluster name	Digital Profile characteristics	Recommended interventions	Alignment with career trajectories
Digitally Advanced	High tool usage, frequent training, <35 years	Leadership training, cross-ministry project assignments	High promotion probability within 3–5 years
Competent Practitioners	Moderate digital skills, mid-career professionals	Skill upgrade courses (AI, data analysis), peer mentoring	Lateral mobility or specialization paths
Traditionalists	Low digital usage, nearing retirement	Basic digital literacy training, transition support workshops	Gradual exit or advisory roles
Development Needed	Poor evaluations, low tech engagement	Foundational e-learning modules, structured mentoring	Early-stage support to reduce attrition risk

The recommender system was implemented using collaborative filtering applied to synthetic civil servant profiles. It generated cluster-specific training and mentorship recommendations that aligned with observed or expected career trajectories. For instance, the "Digitally Advanced" cluster was matched with high-skill leadership tracks that is supporting their upward mobility potential and the "Development Needed" group received foundational digital literacy interventions to mitigate attrition risks. The precision of recommendations was validated by their consistency with historical promotion and performance trends embedded in the dataset. These findings demonstrate that AI-powered personalization tools can enhance civil service training efficiency by aligning capacity-building efforts with employee profiles and career stages. Personalization tools like recommender systems, while effective in tailoring interventions, must be regularly audited to ensure that they do not systematically disadvantage specific employee profiles based on age, region or background. Ethical AI governance frameworks are therefore essential to prevent feedback loops that might reinforce underrepresentation. The findings of the current study provide robust evidence addressing all four research questions. First, RQ1 is affirmed by demonstrating the technical feasibility of AI integration into civil service HCM using LSTM and clustering models. The use of technology in decision making was also supported by many studies [38], [39]. RQ2 is validated through the model's high F1-score and AUC that demonstrate suitability for longitudinal career prediction. Same was demonstrated by [40]. RQ3 is addressed through the construction and validation of prototype recommender systems which generated training paths aligned with each cluster [41]. RQ4 is supported by qualitative and econometric results indicating moderate institutional readiness, with clear policy intent but operational limitations. It is answered by combining qualitative findings (e.g., fragmented systems, policy support without operational frameworks) with econometric evidence of significant performance gains from digital tools. That suggests readiness in intent but not in infrastructure or skills.

When compared globally, Kazakhstan lags behind Singapore in terms of adaptive learning systems and behind Estonia in terms of data interoperability and ethical oversight. Nevertheless, the progress made under Digital Kazakhstan provides a foundation upon which intelligent HR tools can be piloted and scaled.

The study offers three novel contributions that are summarized in Table 6. First is the application of deep learning to predict career paths in a post-Soviet bureaucracy. Second is the introduction of data-driven clustering to inform civil service training policy and third is the conceptual advancement of “digital HC” as a measurable and operational framework for AI integration in public HRM.

Table 6. Key research contributions and innovations

Contribution	Description
Career Forecasting via AI	First use of LSTM for civil servant trajectory prediction in Kazakhstan
Digital Competency Clustering	Segmentation of staff for personalized learning pathways
Digital Human Capital Operationalization	Defined indicators and tools for measuring and enhancing state HR capabilities

This study refines the concept of digital HC by treating it as a dynamic, multidimensional framework. It moves beyond static qualifications to include factors like digital tool use, AI responsiveness, and institutional readiness, highlighting how civil servants actively shape and adapt to evolving algorithmic systems within modern public administration.

Limitations of the current study include reliance on synthetic data due to access constraints, risk of bias in AI predictions, and challenges in interpretability of deep learning models. The way to mitigate them is by recommending institutional data partnerships, use of SHAP for model transparency, and triangulation with interpretable models (e.g., decision trees) in future iterations.

3.3. Implications

This study has both practical and theoretical implications. The recommendations are prioritized into short-, mid- and long-term steps, as below:

Short-term: Create a national digital competency framework: Standardize expectations for digital engagement and align training programs with the four competency clusters identified through K-means analysis (RQ3). Responsible stakeholders: Civil Service Agency, Ministry of Education and Science. Challenges: Senior staff resistance; lack of standardized data. Indicators: % of ministries adopting the framework; number of training programs aligned with cluster needs.

Upskill HR professionals in AI and data analytics: Address the moderate institutional readiness and skills gap revealed in the qualitative findings (RQ4). Responsible stakeholders: Ministry of Digital Development, Civil Service Academy. Challenges: Budget constraints; shortage of AI expertise. Indicators: Number of HR officers trained; integration of AI ethics and analytics into HR curricula.

Mid-term: Establish AI innovation labs in ministries: Pilot AI-based HR tools such as LSTM models and recommender systems to build internal capacity (RQ2 & RQ3). Responsible stakeholders: Ministry of Digital Development, selected pilot ministries. Challenges: Coordination across ministries; technical infrastructure. Indicators: Number of AI prototypes tested; % of ministries piloting intelligent HR systems.

Develop interoperable HR information systems: Overcome the fragmented data infrastructure identified in Kazakhstan's civil service case study (RQ4). Responsible stakeholders: Ministry of Digital Development, National IT Center. Challenges: Integrating legacy databases; ensuring data security. Indicators: % of ministries using centralized HR platforms; reduction in manual HR processes.

Long-term: Embed AI-driven personalized training and career forecasting tools nationwide: Scale the LSTM predictive models and collaborative filtering recommender systems validated in the study (RQ2 & RQ3). Responsible stakeholders: Civil Service Agency, Ministry of Labor. Challenges: Ensuring algorithmic fairness; sustained funding. Indicators: Employee satisfaction scores; promotion equity measures.

Establish ethical oversight bodies for AI in public HRM: Mitigate risks of bias and build public trust in AI-supported HR systems (RQ2 & RQ4). Responsible stakeholders: Parliament, Ministry of Justice. Challenges: Balancing transparency with confidentiality; defining oversight scope. Indicators: Number of AI audits conducted; public trust ratings on algorithmic governance.

4. Conclusions

The current study developed a comprehensive framework for integrating artificial intelligence (AI) and neural networks into human capital management (HCM) in civil service of Kazakhstan. It advances the concept of digital HC by combining employee digital competencies with institutional capacity for AI-driven HR systems. This operationalization links algorithmic personalization to public sector modernization and offers a new perspective for post-Soviet administrative reform (RQ1).

Findings of this work provide strong support for AI's potential in public HRM. Long short-term memory (LSTM) models achieved high predictive accuracy in forecasting career trajectories ($F1 = 0.84$; RQ2). Moreover, K-means clustering identified four distinct digital competency segments that enable differentiated training interventions. Also, the econometric analysis demonstrated that digital HR systems significantly enhance performance with digitalization effects surpassing those of tenure (RQ3). However, qualitative evidence revealed only moderate readiness for adoption for AI that is constrained by fragmented infrastructure, insufficient technical expertise and cultural resistance to algorithmic decision-making (RQ4).

One notable insight was the lack of a significant relationship between tenure and performance. This challenges traditional seniority-based promotion models and suggests that in a digitized HR environment, adaptability and engagement with digital tools play a greater role in driving merit than years of service. It highlights the need to shift evaluation criteria toward continuous learning and digital competency as core indicators of effectiveness.

Policy recommendations include developing interoperable HR information systems, launching AI pilot programs such as recommender systems and digital assistants and investing in targeted upskilling for HR professionals and civil servants. Establishing ethical oversight mechanisms is essential to ensure algorithmic fairness and build trust in automated HR processes.

Limitations of this work include restricted access to official datasets, potential survey bias and the Kazakhstan-specific scope. Future research should examine blockchain-integrated AI for secure, transparent HR data management and conduct cross-country comparisons within post-Soviet and developing contexts to refine and validate the framework. These insights contribute to global debates on AI-driven public sector innovation and responsible digital governance for Kazakhstan and for rest of the world.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

The contribution to the paper is as follows: A. Shakhshina, R. Bugubayeva, Y. Stavbunik: study conception and design; R. Bugubayeva: data collection; A. Shakhshina, R. Bugubayeva: analysis and interpretation of results; A. Shakhshina, Y. Stavbunik: draft preparation. All authors approved the final version of the manuscript.

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