JOURNAL OF CULTURAL ANALYSIS AND SOCIAL CHANGE

Journal of Cultural Analysis and Social Change,
2025, 10(4), 1160-1176
ISSN: 2589-1316

Does Government AI Readiness Improve Human Resource Management Efficiency in The Public Sector?

Aigerim Amirova[1*], Saule Iskendirova[2], Azamat Zhanseitov[3*], Aliya Daueshova[4], Zhansaya Zhunissova[5]

[1] *Assistant Professor, Astana IT University, Astana, Republic of Kazakhstan*
[2] *PhD, Associate Professor, Academy of Public Administration under the President of the Republic of Kazakhstan, Astana*
[3] *Associate Professor, Academy of Public Administration under the President of the Republic of Kazakhstan, Astana*
[4] *PhD, Head of the Competence Assessment Sector of the Institute of Human Resource Management of the Academy of Public Administration under the President of the Republic of Kazakhstan, Astana, Republic of Kazakhstan*
[5] *Master of science, Karaganda Higher Polytechnic College, Karaganda, Kazakhstan*

***Corresponding Author:** A.Amirova@astanait.edu.kz, a.zhanseitov@apa.kz

Citation: Amirova, A., Iskendirova, S., Zhanseitov, A., Daueshova, A., & Zhunissova, Z. (2025). Does Government AI Readiness Improve Human Resource Management Efficiency in The Public Sector?. *Journal of Cultural Analysis and Social Change*, *10*(4), 1160–1176. https://doi.org/10.64753/jcasc.v10i4.2995

Published: December 08, 2025

ABSTRACT

The research purpose determined for this study focuses on investigating whether and to what extent AI readiness levels of public sector institutions affect their HRM efficiency. In doing so, the secondary objective for this research concentrated on observing the heterogeneity determined by national differences at the global level. This research used panel data from 45 countries selected based on the data available for their AI readiness index from Oxford Insights per annum, and their government effectiveness from the World Bank indices per annum. The data was then statistically examined using the multi-linear regression (MLR) model. Information was also gathered by reviewing literature on the research problem. The findings obtained from the research revealed that AI readiness is directly responsible for the HRM efficiency level retained by the public sector organizations. However, there were notable discrepancies when observing the effects of total AI readiness scores, the technology sector, and data and infrastructure, which were excluded from the model. Nonetheless, the findings rejected the null hypothesis for this research, implying that HRM efficiency is indeed affected by the AI readiness of public organizations. The findings obtained from this research can be used to develop policy decisions that focus on strengthening AI readiness and accomplishing maturity levels, while also focusing on HRM efficiency enhancement strategies. Considering each HRM dimension in alignment with the drivers identified through the AI readiness framework will be highly beneficial in this regard. This research is a novel approach to utilize 45-country panel data spanning 4 years (from 2020 and 2023), further deconstructing AI readiness into ten distinct dimensions.

Keywords: Government AI Readiness, Human Resource Management (HRM), Public Sector Efficiency, Digital Transformation, Policy Implementation

JEL Classification Codes: O33 (Technological Change: Choices and Consequences); H83 (Public Administration; Public Sector Accounting and Audits); M12 (Personnel Management; Executive Compensation)

INTRODUCTION

One of the most recent advances in technology innovation has been the development of Artificial Intelligence (AI), which is being used extensively as a tool in critical decision-making. The current era is often defined as the era of information, where digital tools and platforms play a key role in accumulating, storing, and managing large volumes of data, which support evidence-based decision-making, while also adding the benefits of cost and time efficiency to the process. As is observed, the resourceful utility of AI has allowed it to impact a multitude of sectors, including governmental domains. Nonetheless, AI also raises certain ethical concerns, such as the authenticity of the data quality presented through the technique, its potential for biases, lack of explainability, and others. As a result, institutions looking forward to integrating AI in their operational framework need to emphasize their readiness in order to retain the intended strategic benefits.

Irrespective of the underlying challenges concerning the integration of AI in the public sector, it has emerged as a defining trend in the context, as a need to tether modernization while maintaining pace with global transformations. Arguably, the goal of AI integration into the operational frameworks of public sector institutions includes improving the overall service delivery efficiency, addressing complex problems that require in-depth data-based assessment and decision-making, and streamlining administrative procedures to identify and eliminate gaps with the highest degree of efficiency. In all these functions, Human Resource Management (HRM) practices sit at the core, driving digital transformation through AI integration in all spheres. As HRM is often perceived as the fundamental measure for the multidimensional functionality of the organizational operations, reflecting its adaptability, agility, and competitiveness in integrating and managing progressive changes, it is essential that institutions take due diligence in building their HRM readiness when seeking to utilize AI in its full capacity.

This study is intended to investigate whether, and the extent to which, AI readiness of the government can translate into tangible gains for HRM efficiency for the public sector. The underlying fundamental assumption for this research argues that effectiveness in AI readiness for the public sector can directly influence organizational HRM efficiencies in terms of recruitment, training, performance evaluation, and administrative procedures within the public sector. Correspondingly, this research draws from various global indices and previously conducted empirical investigations to identify and elaborate on the common themes emerging from the public sectors of various economies, such as India, the US, the UK, Singapore, and others. In doing so, this research offers valuable and comprehensive insights into the enablers, barriers, mechanisms, and future scope of improvements for AI-driven HRM strategies being executed by the public sectors of these nations. Therefore, this research presents a multi-regional perspective on the contributions of their AI readiness to drive HRM efficiency within the public sector.

The objectives of this research are to –

- Examine the extent to which AI readiness prevails across the public sector institutions of different countries around the world
- Statistically and theoretically comprehend the correlation between AI readiness and HRM efficiency within the public sector
- Explore the enablers and barriers affecting AI readiness of public sector institutions and subsequently, influencing their HRM efficiency

The questions thus focused on this research to accomplish the above-listed objectives are as follows:

- RQ1 – Do AI readiness affect HRM efficiency within public sector institutions across the globe?
- RQ2 – To what extent does HRM efficiency in the public sector institutions affect their AI readiness?
- RQ3 – What common patterns and trends emerge from the AI readiness and HRM efficiency initiatives of public sector institutions across different countries?

Definitions for Key Terms

AI Readiness: AI can be observed as generative and ambidextrous at the same time, considering its multidimensional and simultaneous impacts on an array of operational procedures, ranging from the optimization of already established decision-making frameworks to the personalization of services to ensure overall effectiveness in consumer satisfaction and retention (Zhou et al., 2025). A major barrier to these adaptations is the lack of infrastructural sufficiency and supporting mechanisms that boost AI adaptation efficiency at large, which can be eliminated through AI readiness. Precisely, AI readiness not only seeks to enhance digital infrastructure and mechanisms but also establishes leadership perceptions, regulatory robustness, innovation capacity, and data ecosystem maturity, offering an all-inclusive and sustainable solution to the challenges linked with the integration of AI (Tehrani et al., 2024). In the context of this research, the term AI readiness implies the ability of the public sector to efficiently and responsibly adopt AI tools, which is further reflected in their sustainability scope.

HRM Efficiency: HRM is concerned with the people management strategies being applied within the organizational context to optimize the functioning of human resources working at the institution (Cicek & Demir, 2015). HRM efficiency, therefore, refers to the balance accomplished between the costs and resources used to recruit, train, manage, and optimize the human resources within the organization, and ensure the desired level of outcomes from these initiatives. Overall, the term indicates the operational, strategic, developmental, and administrative efficiencies retained by the organization through its HRM decisions (Phillips, 2021).

Public Sector: The term, public sector, refers to the broad category of government-funded and operated institutions, established solely with the purpose of rendering public services. These institutions are thus designed to execute multiple functions, ranging from enforced regulations to the implementation of national, regional, and local policies in the best interest of the public.

Global AI Readiness Indices: Observably, both HRM and AI concepts indicate complex and broad-scale practices, which often inhibit the degree of comprehensiveness required throughout the interpretation (Amirova et al., 2025). To ensure comprehensiveness in the process of collecting and interpreting the data gathered in this research, in alignment with these practice dimensions, the integration of leading global AI readiness indices has been of substantial importance. These indices function as comprehensive benchmarking tools, offering comparative insights into the AI readiness of different countries to improve their HRM efficiency in the public sector. For example, the Oxford Insights Government AI Readiness Index (2024) assesses more than 190 countries based on three pillars of AI readiness, i.e., government, technology sector, and data & infrastructure. Focusing on the governmental parameter, the index compares national AI strategies, their digital capacity, regulatory and ethical frameworks, and their adaptability. For the technology sector parameter, human capital, the maturity of the technology sector, and the innovation environment of the nations are scaled. Correspondingly, for the data & infrastructure parameter, data availability, digital service quality, and sufficiency of the IT Infrastructure are measured. The index thus offers various dimensions to compare and contrast the degree of AI readiness of the sample countries, with a focus centered on their HRM practices.

LITERATURE REVIEW

According to Russell & Norvig (2021), Artificial Intelligence (AI) can be observed from different perspectives, making it difficult to be defined comprehensively. In the broadest sense, although AI has often been linked with the use of big data algorithms, Russell & Norvig (2021) and Sheikh et al. (2023) argued that algorithms have been used for decision-making purposes long before the invention of AI. Narrowing down on the characteristics of AI, Sheikh et al. (2023) affirmed that previous attempts to define the technology have rendered a limited scope and relevance to a heterogeneous range of studies across different fields of expertise. Gradually, Sheikh et al. (2023, p. 19) settled for the definition of AI by AI HLEG, asserting that AI refers to "*systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals*".

Offering a fresh perspective on the concept of AI, Saghiri et al. (2023) argued that since its introduction, AI has been used in different spectrums of the modern-day socio-economic environment, redirecting emphasis to its dominant branches, including Artificial Super Intelligence (ASI), Artificial General Intelligence (AGI), and Artificial Narrow Intelligence (ANI). When elaborating on the concept of ASI, Saghiri et al. (2023) stated that there are three forms of ASI currently being used, which include speed ASI, where the computer or the agent solves the problem faster than humanely possible, collective ASI, where the agent multi-tasks into finding the most appropriate solution for the problem, similar to a group of humans, and quality ASI, where agents are equipped to execute tasks considered nearly impossible for humans within the given time and space. AGI, on the other hand, refers to the systemic use of advanced technology to execute tasks that require highly skilled humans, while ANI are applications of AI concentrated on resolving a specific problem, such as playing games, face recognition, and similar others (Saghiri et al., 2023).

Public sector readiness to adopt AI has largely focused on the ASI category, where AI technology is designed to perform a multitude of tasks with accuracy within a given timeframe, utilizing sufficient resources. Contextually, however, defining AI Readiness is equally challenging as defining AI. According to Jöhnk et al. (2020), AI readiness also concerns large-scale changes across the organizational framework, which makes it a complex theoretical framework integral to challenges related to the practical execution of the technology. Jöhnk et al. (2020) argued that AI offers the potential to solve issues related to a variety of problems, ranging from clinical decision-making, autonomous vehicles as well as virtual assistants, mandating that organizations planning to use this tool need to rethink their decision-making procedures to align with the technological protocols inherent in the AI design. Stating precisely, Jöhnk et al. (2020, p.8) emphasized that "*AI's variety of adoption purposes requires organizations to create the necessary conditions, and introduce managerial practices for successful AI adoption*". Below is a diagrammatic illustration offered by Jöhnk et al. (2020, p.9), illustrating the key conceptual properties of AI readiness, which can be translated into a structured AI readiness framework.

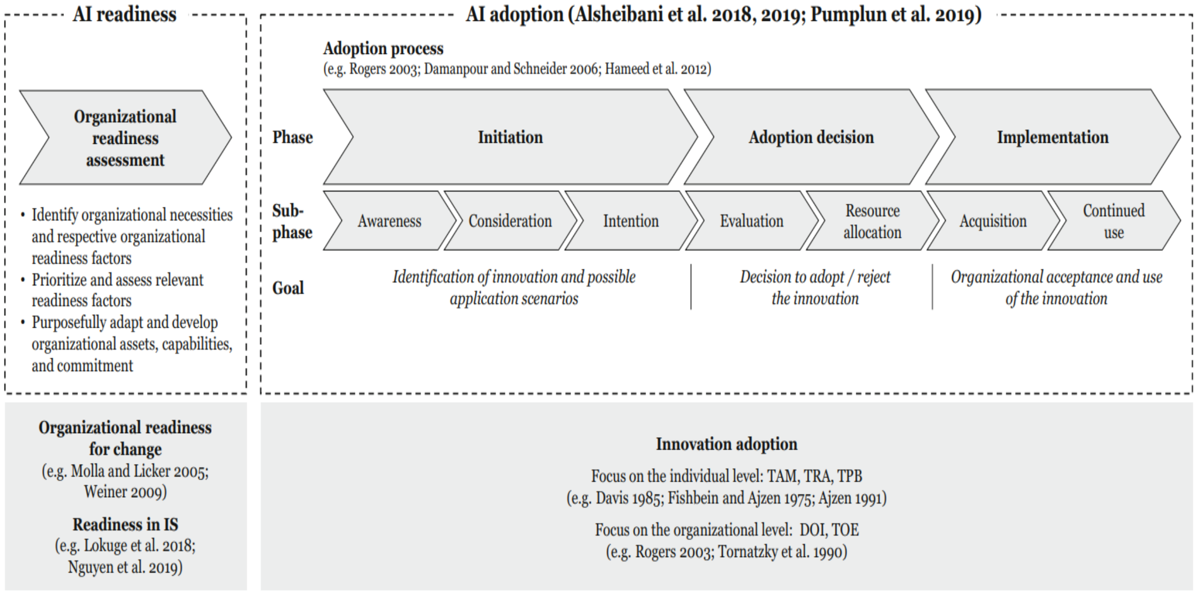

Figure 1. AI Readiness Conceptual Framework (Jöhnk et al., 2020, p.9)

As can be observed from Figure 1, the readiness of organizations to adopt AI can be attested based on the alignment between the use of AI and the operational necessities of the organization, prioritization and examination of organizational readiness factors, and strategically focused adaptation, as well as development of the assets, capabilities, and commitment of the organization. The diagram also exhibits that AI adoption is a gradual process whereby the organization evolves from initiation to the implementation of AI strategies across the organizational framework. From a critical perspective, Jöhnk et al. (2020) deduced that AI readiness depends on factor identification, harmonization, and categorization, as well as indicator development and validation, which was also diagramatically presented by these authors.

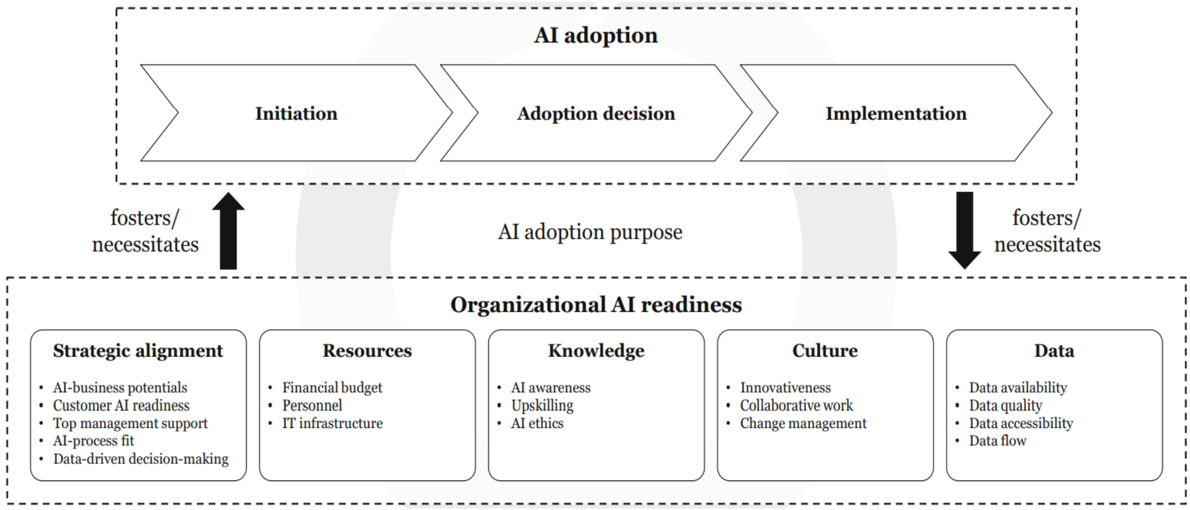

Figure 2. AI Readiness Framework (Jöhnk et al., 2020, p.17)

Elaborating further, Lee et al. (2024) emphasize that public sector organizations differ from the private sector in terms that they assume a greater degree of responsibility in contributing to public welfare, while functioning with human resource constraints and budget limitations. According to Lee et al. (2024), the AI readiness of the public sector organizations depends on three specific criteria, based on the case observation of Singapore. Firstly, Lee et al. (2024) argued that a nationwide policy consideration is necessary to ensure the full-fledged integration of AI at all levels of public service, which will help to ensure that at the national level, the AI system is well aligned with its infrastructural requirements and its future goals to improve its overall performance. Secondly, the AI readiness score of the nation is also dependent on its logistical partnerships, offering the public agency a stake in the competitive environment of the technology sector (Lee et al., 2024).

For instance, the Singaporean government has partnered with Microsoft and other companies offering AI services in the global arena, making the agency aware of international developments in the context, and allowing the government to integrate AI inventions with the best of its capabilities (Lee et al., 2024). Thirdly, the public agencies in Singapore also required to ensure the adaptability of its social environment, considering that the public were apparently taking an increasing interest in the simplification and exclusion of bureaucratic complications to improve their convenience, which is why the government has continued its investments in managing their social reach through social media platforms using AI-based solutions (Lee et al., 2024). Below is a comprehensive exemplification of the findings obtained by Lee et al. (2024), with emphasis on AI readiness of the Singaporean public sector agencies.

Table 1. Environmental Factors Delivering AI Readiness (Lee et al., 2024)

Sub-criteria under Organisational Context	Definition	Assessment if meet criteria
Regulatory environment Terms: IM8, data classification	Governance refers to the regulatory environment that the government agency has to comply with. With proper and supportive governance, the agency will likely be more ready to implement AI-enabled technologies [Pudjianto et al., 2011].	The agency can assess its readiness by reviewing the AI-enabled technologies that the agency is keen to adopt that are compliant with regulations.
Nation mandate Terms: digital blueprint, IMDA, Govtech	Nation Mandate refers to the overall direction that the nation or country is moving towards. If the whole government is moving towards digitalisation and adoption of AI-enabled technologies, the agency is likely to implement such technologies.	The agency can assess its readiness by reviewing if there is a structured national mandate in place.
Competitive environment Terms: private, new technology, blockchain	Competitive environment is defined as the landscape that the agency is in. If the private sector implements more AI-enabled technologies, this will accelerate the government agency to consider adopting such innovations [Zhu et al., 2003].	The agency can assess its readiness by comparing its current technology stack against the technology products available in the market.
Social approach Terms: social media	The social approach is defined as the social media platforms present in the current environment. The more such platforms exist, the more likely the government agency will consider implementing AI-enabled technologies to reach out to the citizens as an effective way to increase the target base of the organisation [Chatterjee et al., 2019].	The agency can assess its readiness by reviewing the number of social platforms that the government agency is engaging its citizens with. The higher the number of social platforms, the higher the probability that their officers are savvy enough to consider AI-enabled technologies.

Similar findings have been observed by other investigations into the environmental drivers leading to AI readiness within the public environment. For instance, Neumann et al. (2024) argued that public organizations have specific challenges to overcome to integrate AI readiness, which can be comprehended using the Technology Organization Environment (TOE) framework. Lee et al. (2024) and Neumann et al. (2024) align in their inferences, thus affirming that the drivers of AI readiness depend largely on technological, organizational, and environmental maturity of the public agencies, allowing them to use the most reliable and effective AI techniques. Neumann et al. (2024) also discussed the five levels of AI readiness maturity of public agencies that determine their AI effectiveness at different levels, which include the initial, assessing, determined, managed, and optimized levels, as exhibited in Table 2 below.

Table 2. AI Readiness Maturity Levels (Neumann et al., 2024)

Level	AI functions
Initial	Very limited or no AI function, and the organization has no plans to use AI.
Assessing	Discovery of AI technology.
Determined	AI project is at an advanced stage; determination of infrastructure needed to further implement AI.
Managed	Certain AI processes are defined throughout the organization. Preparation of large-scale AI application.
Optimize	Full AI infrastructure is ready for large-scale AI application.

Diving deeper into the context of AI readiness and its driving factors, Campion et al. (2020) identified the challenges faced by public agencies, restricting their maturity level, as were asserted by Neumann et al. (2024). These challenges include privacy/security concerns, misalignment between project expectations and interests, a lack of data understanding, and bureaucratic obstacles at the primary level, suggesting that these organizations often struggle with their preconceived notions about data breaches, undermining their need for sharing data without jeopardizing data security (Campion et al., 2020). Public organizations are also often in need of inter-departmental and inter-organizational collaboration to ensure effectiveness through AI integration across all sections, leading to bureaucratic complications, delaying their maturity level for AI readiness (Campion et al., 2020).

Uren & Edwards (2023) also opined that AI readiness within the public sector organizations depends largely on people, process, and technology, and the way these three dimensions correspond with each other, supporting the findings obtained by Lee et al. (2024), Neumann et al. (2024), and Campion et al. (2020). As was further observed by Saghiri et al. (2022), while there are challenges related to security, fairness, transparency, robustness, and energy consumption, emphasis on these barriers often tends to obstruct the overall AI readiness of public agencies, similar to what was observed by Campion et al. (2020).

Notably, the AI readiness framework is built upon these observations of challenges faced by public agencies when integrating AI technologies within their organizational structure. For instance, Holmstrom (2022) presented an AI readiness framework that concentrates on recording and assessing the changes initiated by the government under four dimensions. The first dimension taken into consideration by Holmstrom (2022) is the technology dimension, whereby the AI readiness framework assumes that the public organizations need to adapt to changes relevant to the effective integration of AI technologies, while the second dimension emphasises the changes required in terms of activities necessary to maintain the pace of the agency with the evolution of digital technology in the global context (Holmstrom, 2022). The other two dimensions concentrated in the AI readiness framework by Holmstrom (2022) include boundaries and goals. To integrate AI transitions at the boundary level, public agencies are required to observe and address their infrastructural requirements while also partnering with other agencies to address the gap, thereby ensuring long-term sustainability (Holmstrom, 2022). As for goals, the agencies are required to make changes in their policy considerations, which are also aligned with the other three dimensions (Holmstrom, 2022). Below is the diagrammatic representation of the AI readiness framework suggested by Holmstrom (2022).

Figure 3. AI Readiness Framework (Holmstrom, 2022)

However, it must be emphasized in this context that the AI readiness framework suggested by Holmstrom (2022) vaguely addresses the observed drivers at the environmental, technological, and structural levels. The scoring system can also be argued as deeply flawed, being highly dependent on a self-administered questionnaire (Holmstrom, 2022), making it prone to biases and hence unreliable. In contrast, the observations and suggestions presented by the Digital Education Council on the AI readiness framework offer valuable insights by focusing on ten distinct dimensions, which include (i) strategic alignment, (ii) institutional governance, (iii) stakeholder engagement, (iv) operational readiness, (v) AI literacy and ethical use, (vi) accessibility and inclusion, (vii) faculty and administrative professional development, (viii) teaching, learning, and assessment strategies, (ix) curriculum development and workforce alignment, and (x) research and innovation (Digital Education Council, 2025). To structure the AI readiness framework, the Digital Education Council duly emphasized the four levels of AI readiness, which are in alignment with the findings in Neumann et al. (2024). The levels considered by the Digital Education Council (2025) have accordingly been illustrated in the table below.

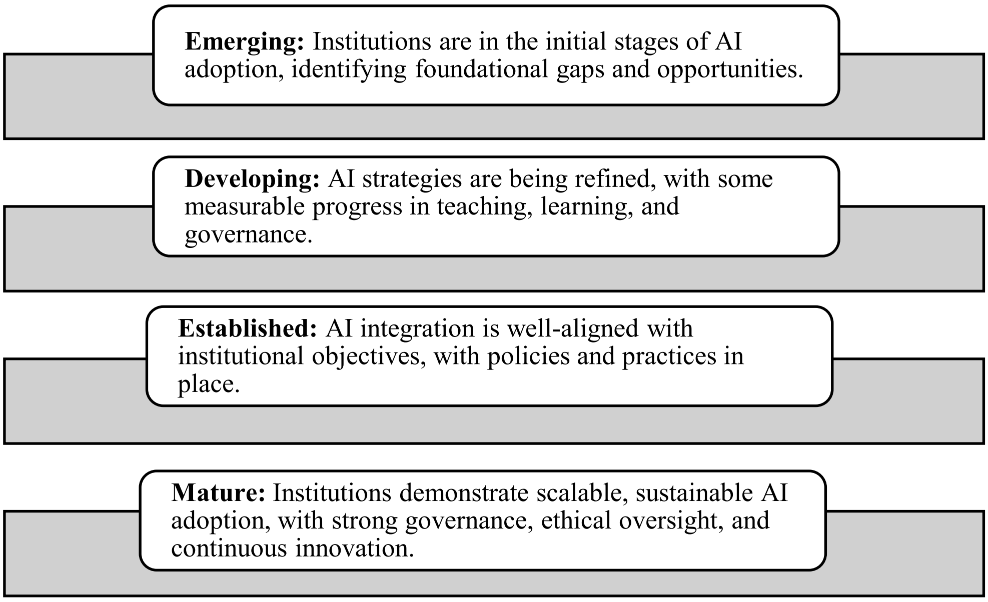

Figure 4. AI Readiness Levels Identified by the Digital Education Council (2025)

Alignment of the AI technologies being considered for the organization with its strategic priorities of the present, short-term, mid-term, and long-term has been widely recognized in academia for its significance in ensuring the overall AI readiness maturity of the agencies. The qualitative measures used by Jokinen (2025) to assess the AI readiness of an organization based on its strategic alignment revealed that maturity in this dimension allows the agencies a greater scope for goal accomplishment through a systematic and focused transition. Observations from Felemban et al. (2024) also argued that strategic planning is an integral part of the front-end planning (FEP) when it comes to AI readiness levels of organizations. Studies have also complemented the association between institutional governance and AI readiness of the organizations (e.g., Neuwirth, 2024; Socol & Iuga, 2024; Nzobonimpa & Savard, 2023), with attention to transparency and governance efficiency as the common themes. Stakeholder engagement is another dimension that has been widely explored to assess AI readiness in organizations, whereby authors have argued about its significance from the lens of skill enhancement through formal and effective training and organizational cultural change management (Kopallé et al., 2023; Alami et al., 2020).

In contrast, emphasis on operational readiness has not received comparable significance in academia, indicating a probable literature gap. Correspondingly, however, when emphasizing AI literacy and ethical use as a driver for AI readiness, existing studies conducted can be observed to overlap with the concepts of stakeholder engagement, implicitly addressing the HRM efficiency requirements throughout the change process and the integration of AI (Özüdoğru & Durak, 2025; Chatikobo & Pasipamire, 2024). Elaborations and explanations for accessibility and inclusion have also been restricted in academia, although in the two instances where this dimension is taken into consideration, the human resource perspective gained greater significance than infrastructural aspects (Shonhe et al., 2024). Similar literature gaps have also been observed with respect to the dimensions of faculty and administrative professional development, teaching, learning, and assessment strategies, curriculum development and workforce alignment, and research and innovation.

From a critical perspective, referring to the justifications and the criteria specified by the report from the Digital Education Council (2025) on the AI readiness framework aligned with AI maturity levels of the organizations, all ten dimensions listed and discussed above are entwined with the HRM efficiency retained by the agencies, further leading to the understanding that AI readiness draws leadership attention to HRM integration, therefore ensuring overall HRM efficiency. The perception has been presented with deep consideration of the use of AI technologies in the process of managing human resources in recent research works as well. For instance, Stor (2023) presented that private organizations, both large and medium-sized, are investing substantially to assess employee performance, identify gaps, plan skill improvement strategies, and implement measures that would largely benefit the targeted organizational goals. Madanchian (2023) also affirmed that AI tools are being extensively used by organizations to redefine HRM paradigms, ranging from recruitment process optimization and training requirements to employee engagement and retention. Alsaif & Aksoy (2023), on the other hand, reflected the impacts of AI in reducing the workload of human resources, thereby preventing the risks of erroneous decision-making, conflict, and early burnout, while also enhancing inter-departmental and inter-organizational collaborations (Mohamed et al., 2022; Muqaddim & Hosain, 2021).

In summary, the existing literature suggests that AI readiness within public sector organizations is inherently multidimensional, spanning across the domains of technological innovation, governance efficiency, and workforce capabilities. While the first two domains are primarily concerned with the infrastructural and systemic qualities of AI innovations, this research is specifically focused on assessing the contributions of AI readiness of public organizations in driving their workforce capabilities, termed as their HRM efficiency levels (Ibadildin et al., 2025). A common theme that emerged from the reviewed literature was the lack of understanding about the definitive characteristics of AI, especially when being used by public sector organizations. This is also reflected in the lack of adequate understanding and definitions available to explain the concept of AI readiness, further resulting in a literature gap for this research context. Nonetheless, public sector organizations have been observed to progress gradually at five levels to achieve AI readiness maturity that is aligned with the TOE model, leading to the development of the AI readiness framework with ten dimensions, as per the suggestions of the Digital Education Council. Irrespective of these developments in the understanding of AI readiness in academia, a gap was observed in the literature. Precisely, emphasis on the effects of AI readiness in driving HRM efficiency for public sector organizations remained limited in the literature, even though the AI readiness framework and levels of maturity identified the significance of employee engagement, people management, stakeholder engagement, and other aspects of HRM efficiency.

RESEARCH METHODOLOGY

The fundamental goal of this research is to assess the impacts of AI readiness on the HRM efficiency of public sector organizations across different countries around the world. It was thus that this research took reference from the Digital Education Council (2025), which presents that organizations can be categorized into five levels of maturity to determine their AI readiness (Figure 4) and ten dimensions to score their AI readiness. Correspondingly, the government AI readiness index was used to gather panel data from Oxford Insights, for the last five years, from 2020 to 2024. It is worth mentioning that Oxford Insights publishes annual reports on the AI readiness scores of 188 countries (Fuentes et al., 2024). Currently in its 7th edition, the government AI readiness index measures datasets across leading organizations, such as the UNESCO and G20. The dataset is presented in the index based on three pillars (i.e., government, technology sector, and data and infrastructure) and ten dimensions, including vision, governance and ethics, digital capacity, adaptability, maturity, innovation capacity, human capital, infrastructure, data availability, and data representativeness (Fuentes et al., 2024). In constructing the index, Oxford Insights assesses 40 indicators relevant to these variables, making the data source as thorough as possible (Fuentes et al., 2024). Below is a diagrammatic representation of the AI readiness index used for this research.

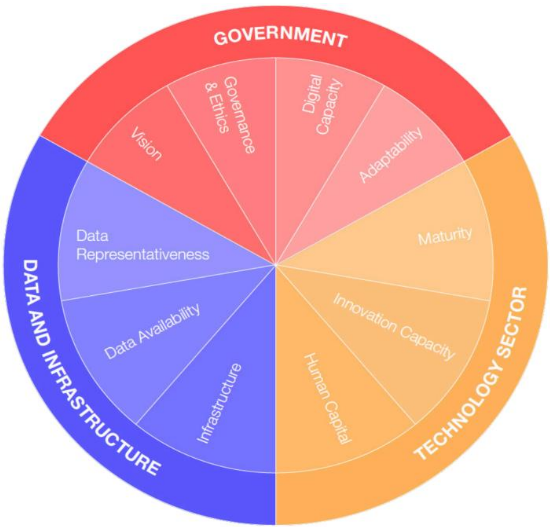

Figure 5. The pillars and dimensions of the Government AI Readiness Index (Fuentes et al., 2024)

However, for this research, the dimension of vision was excluded, based on the observation that the scores were generally either 0 or 100 for the countries, implying limited to no significance for the total score secured by each country. This research also limited the sample countries to 50 (N = 50). Correspondingly, the non-probability purposive sampling strategy was used in this research, whereby the first 50 countries from the government AI readiness index 2024 were confirmed as the sample. Subsequently, the list was cross-referenced with the previous indexes for 2023, 2022, 2021, and 2020, leading to the elimination of countries that were not listed or had blank data. This was a necessary step to ensure overall rigor in the process of statistically evaluating the data. Finally, the sample size considered for this research was 45 (n), spanning across 5 years. The same list of 45 countries was used to gather the data for government effectiveness from the World Bank (2024). However, it is worth mentioning that the data retrieved from the World Bank (2024) lacked data for the same period as that for the government AI readiness index, with the latest data available as of 2023, but not later. This led to the concentration of the panel data for four years, from 2020 to 2023, for the regression analysis. Nonetheless, the dataset offers sufficient heterogeneity across the panel data, in addition to ensuring temporal dynamics and cross-country variations, which in turn increases the robustness and generalizability of the findings obtained from this econometric study.

For the multi-linear regression (MLR) analysis, the government effectiveness (GE_t) score was used as the dependent variable, while the variables pertaining to the three pillars and ten dimensions, along with the total score [i.e., Total Scores (TS_t), Government ($Govt_t$), Technology Sector ($Tech.S_t$), Data and Infrastructure ($D\&I_t$), Governance and Ethics ($G\&E_t$), Digital Capacity (DC_t), Adaptability ($Adty_t$), Maturity ($Maty_t$), Innovation Capacity ($Inv.C_t$), Human Capital ($H.Cap_t$), Infrastructure ($Infra_t$), Data Availability ($D.Abty_t$), Data Representativeness ($D.Rep_t$)], were used as the independent variables. The MLR test was carried out for each of the four years, from 2020 to 2023. A regression analysis was also used separately to assess the dependency of GE_t on the total AI readiness score (TS_t) and human capital ($H.Cap_t$), which offered distinguished insights into the probable correlation between AI readiness maturity level and HRM efficiency. For the data interpretation, the general hypothesis framed was that g*overnment AI readiness has no significant effect on public sector HRM efficiency* (H_0, $p < 0.05$). This hypothesis was tested using the different variables from the government AI readiness scores and government effectiveness scores accordingly. Results obtained from the data assessment are presented in the following chapter.

RESULT AND DISCUSSION

Multi-Linear Regression (MLR)

As of the year 2023, the MLR assessment reveals the R-Square value of 0.406 and p-value of 0.33, suggesting that the null hypothesis is rejected, which can be interpreted as confirming that, at least for the referred year, government AI readiness has a significant effect on public sector HRM efficiency. In other words, the variables used for the test reflect that governmental HRM efficiency is dependent on the pillars and dimensions used for the AI readiness index, thereby substantiating the alternative hypothesis in this case. However, it must be taken into consideration that the R^2 value (0.406) dropped significantly for the adjusted R^2 value (0.231), suggesting that there are some variables indicating insignificant to no impact on the dependent variable for the year. Critically observing the statistical outcomes, the MLR model created for this analysis excluded three variables (i.e., total score 2023, technology sector 2023, and data and infrastructure 2023), emphasizing the insignificant partial correlations.

Table 3. MLR - Government Effectiveness: Pillars and Dimensions of AI Readiness Index as of 2023

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.637[a]	.406	.231	16.60387	.406	2.322	10	34	.033

a. Predictors: (Constant), Data Representativeness 2023, Government 2023, Data Availability 2023, Innovation Capacity 2023, Digital Capacity 2023, Human Capital 2023, Governance and Ethics 2023, Adaptability 2023, Maturity 2023, Infrastructure 2023

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6400.601	10	640.060	2.322	.033[b]
	Residual	9373.407	34	275.688		
	Total	15774.008	44			

a. Dependent Variable: Government Effectiveness 2023

b. Predictors: (Constant), Data Representativeness 2023, Government 2023, Data Availability 2023, Innovation Capacity 2023, Digital Capacity 2023, Human Capital 2023, Governance and Ethics 2023, Adaptability 2023, Maturity 2023, Infrastructure 2023

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	35.183	45.693		.770	.447	-57.677	128.043
	Government 2023	-.153	.449	-.065	-.341	.735	-1.065	.758
	Governance and Ethics 2023	-.703	.386	-.409	-1.823	.077	-1.486	.081
	Digital Capacity 2023	-.455	.554	-.181	-.821	.418	-1.581	.671
	Adaptability 2023	1.286	.513	.601	2.509	.017	.244	2.328
	Maturity 2023	-.009	.457	-.006	-.019	.985	-.937	.920
	Innovation Capacity 2023	.237	.375	.159	.631	.532	-.526	1.000
	Human Capital 2023	.395	.454	.183	.869	.391	-.528	1.317
	Infrastructure 2023	.782	.678	.364	1.154	.257	-.596	2.160
	Data Availability 2023	-.258	.442	-.114	-.582	.564	-1.157	.641
	Data Representativeness 2023	-.050	.497	-.018	-.101	.920	-1.060	.960

a. Dependent Variable: Government Effectiveness 2023

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Total Score 2023	-147.534[b]	-.608	.547	-.105	3.027E-7
	Technology Sector 2023	535.160[b]	1.082	.287	.185	7.106E-8
	Data and Infrastructure 2023	418.942[b]	1.453	.156	.245	2.036E-7

a. Dependent Variable: Government Effectiveness 2023

b. Predictors in the Model: (Constant), Data Representativeness 2023, Government 2023, Data Availability 2023, Innovation Capacity 2023, Digital Capacity 2023, Human Capital 2023, Governance and Ethics 2023, Adaptability 2023, Maturity 2023, Infrastructure 2023

In comparison, the data findings for 2022 reveal a stronger and significant correlation between the dependent and the independent variables. Precisely, the model fit can be observed as better than that observed for 2023, based on the R value of 0.658, the R^2 value of 0.433, and the adjusted R^2 value of 0.266. However, the change observed between the R^2 value and the adjusted R^2 value indicates a higher variability of the data. Nonetheless, the p-value of 0.18 (< 0.05) suggests that the null hypothesis is rejected, confirming that the pillars and dimensions considered for the AI readiness index for 2022 had an unignorable impact on the government's HRM effectiveness for the year. It is also worth mentioning that, similar to the year 2023, the MLR model for 2022 also excluded the same three variables (i.e., total score 2022, technology sector 2022, and data and infrastructure 2022).

Table 4. MLR - Government Effectiveness: Pillars and Dimensions of AI Readiness Index as of 2022

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	Change Statistics F Change	Change Statistics df1	Change Statistics df2	Change Statistics Sig. F Change
1	.658[a]	.433	.266	16.45863	.433	2.598	10	34	.018

a. Predictors: (Constant), Data Representativeness 2022, Government 2022, Infrastructure 2022, Adaptability 2022, Governance and Ethics 2022, Human Capital 2022, Digital Capacity 2022, Maturity 2022, Data Availability 2022, Innovation Capacity 2022

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7036.830	10	703.683	2.598	.018[b]
	Residual	9210.145	34	270.887		
	Total	16246.976	44			

a. Dependent Variable: Government Effectiveness 2022

b. Predictors: (Constant), Data Representativeness 2022, Government 2022, Infrastructure 2022, Adaptability 2022, Governance and Ethics 2022, Human Capital 2022, Digital Capacity 2022, Maturity 2022, Data Availability 2022, Innovation Capacity 2022

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	23.916	37.903		.631	.532	-53.112	100.944
	Government 2022	-.112	.443	-.053	-.252	.802	-1.013	.789
	Governance and Ethics 2022	-.472	.340	-.283	-1.386	.175	-1.163	.220
	Digital Capacity 2022	-.219	.511	-.086	-.428	.671	-1.258	.820
	Adaptability 2022	1.058	.463	.487	2.283	.029	.116	2.000
	Maturity 2022	.013	.446	.008	.029	.977	-.894	.919
	Innovation Capacity 2022	.512	.440	.370	1.165	.252	-.382	1.406
	Human Capital 2022	-.435	.515	-.179	-.844	.405	-1.481	.612
	Infrastructure 2022	.393	.283	.290	1.386	.175	-.183	.968
	Data Availability 2022	-.322	.458	-.151	-.704	.486	-1.253	.608
	Data Representativeness 2022	.430	.451	.175	.953	.347	-.487	1.348

a. Dependent Variable: Government Effectiveness 2022

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Total Score 2022	86.063[b]	.233	.817	.041	1.260E-7
	Technology Sector 2022	469.904[b]	1.187	.244	.202	1.051E-7
	Data and Infrastructure 2022	378.763[b]	1.058	.298	.181	1.298E-7

a. Dependent Variable: Government Effectiveness 2022

b. Predictors in the Model: (Constant), Data Representativeness 2022, Government 2022, Infrastructure 2022, Adaptability 2022, Governance and Ethics 2022, Human Capital 2022, Digital Capacity 2022, Maturity 2022, Data Availability 2022, Innovation Capacity 2022

Focusing on the data for 2021, it can be observed that the MLR model generated for the dependent and independent variables pertaining to the year suggests a strong overall fit with an R value of 0.747, an R^2 value of 0.558, and an adjusted R^2 value of 0.428. Unlike the previous two years, the drop observed for the R^2 value to the adjusted R^2 value can be argued as insignificant, further suggesting in favor of the model fit. Furthermore, with the p-value of < 0.001, the null hypothesis can be rejected with confidence, implying that the government HRM effectiveness is dependent on the pillars and dimensions variables included in the AI readiness index for 2021. Nonetheless, the model did exclude the same three variables (i.e., total score 2021, technology sector 2021, and data and infrastructure 2021) for the third year in a row, based on the insignificant impacts on the dependent variable.

Table 5. MLR - Government Effectiveness: Pillars and Dimensions of AI Readiness Index as of 2021

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.747[a]	.558	.428	13.88505	.558	4.286	10	34	<.001

a. Predictors: (Constant), Data Representativeness 2021, Digital Capacity 2021, Maturity 2021, Government 2021, Data Availability 2021, Human Capital 2021, Governance and Ethics 2021, Adaptability 2021, Infrastructure 2021, Innovation Capacity 2021

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8263.586	10	826.359	4.286	<.001[b]
	Residual	6555.015	34	192.795		
	Total	14818.601	44			

a. Dependent Variable: Government Effectiveness 2021

b. Predictors: (Constant), Data Representativeness 2021, Digital Capacity 2021, Maturity 2021, Government 2021, Data Availability 2021, Human Capital 2021, Governance and Ethics 2021, Adaptability 2021, Infrastructure 2021, Innovation Capacity 2021

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	-45.588	29.361		-1.553	.130	-105.257	14.081
	Government 2021	.211	.327	.134	.645	.523	-.453	.875
	Governance and Ethics 2021	-.369	.265	-.275	-1.393	.173	-.907	.169
	Digital Capacity 2021	-.256	.352	-.153	-.729	.471	-.971	.458
	Adaptability 2021	1.519	.522	.637	2.912	.006	.459	2.579
	Maturity 2021	.335	.293	.221	1.145	.260	-.260	.930
	Innovation Capacity 2021	.566	.408	.364	1.386	.175	-.264	1.395
	Human Capital 2021	-.325	.320	-.218	-1.015	.317	-.976	.326
	Infrastructure 2021	.011	.295	.009	.038	.970	-.588	.610
	Data Availability 2021	-.081	.450	-.033	-.181	.858	-.996	.834
	Data Representativeness 2021	.136	.329	.073	.414	.681	-.533	.806

a. Dependent Variable: Government Effectiveness 2021

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Total Score 2021	-146.935[b]	-.485	.631	-.084	1.448E-7
	Technology Sector 2021	91.185[b]	.173	.863	.030	4.837E-8
	Data and Infrastructure 2021	-191.445[b]	-.586	.562	-.101	1.243E-7

a. Dependent Variable: Government Effectiveness 2021

b. Predictors in the Model: (Constant), Data Representativeness 2021, Digital Capacity 2021, Maturity 2021, Government 2021, Data Availability 2021, Human Capital 2021, Governance and Ethics 2021, Adaptability 2021, Infrastructure 2021, Innovation Capacity 2021

The overall fit observed for the MLR model for 2020 can be observed as strong at R = 0.763, R^2 = 0.583, and adjusted R^2 = 0.460. This implies that more than 50% of the HRM efficiency score (i.e., government effectiveness score) is determined by the pillars and dimensions of the AI readiness index, except for the three variables, i.e., total score 2020, technology sector 2020, and data and infrastructure 2020. The drop between R^2 and adjusted R^2 values also suggests that the model is a good fit, to confirm the statistically significant dependence between the dependent and independent variables. The p-value observed for the model is also < 0.001, leading to the rejection of the null hypothesis, further implying that the government HRM efficiency is dependent on the AI readiness index.

Table 6. MLR - Government Effectiveness: Pillars and Dimensions of AI Readiness Index as of 2020

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.763[a]	.583	.460	13.08128	.583	4.749	10	34	<.001

a. Predictors: (Constant), Data Representativeness 2020, Digital Capacity 2020, Maturity 2020, Infrastructure 2020, Governance and Ethics 2020, Human Capital 2020, Data Availability 2020, Adaptability 2020, Innovation Capacity 2020, Government 2020

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8126.948	10	812.695	4.749	<.001[b]
	Residual	5818.073	34	171.120		
	Total	13945.021	44			

a. Dependent Variable: Government Effectiveness 2020

b. Predictors: (Constant), Data Representativeness 2020, Digital Capacity 2020, Maturity 2020, Infrastructure 2020, Governance and Ethics 2020, Human Capital 2020, Data Availability 2020, Adaptability 2020, Innovation Capacity 2020, Government 2020

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	1.397	20.812		.067	.947	-40.899	43.693
	Government 2020	.163	.309	.136	.526	.602	-.466	.791
	Governance and Ethics 2020	-.339	.236	-.277	-1.436	.160	-.820	.141
	Digital Capacity 2020	-.044	.348	-.031	-.125	.901	-.751	.664
	Adaptability 2020	.981	.352	.613	2.790	.009	.266	1.695
	Maturity 2020	.383	.204	.303	1.883	.068	-.030	.797
	Innovation Capacity 2020	.188	.360	.126	.522	.605	-.544	.920
	Human Capital 2020	-.287	.333	-.176	-.863	.394	-.963	.389
	Infrastructure 2020	-.101	.168	-.088	-.599	.553	-.443	.241
	Data Availability 2020	-.198	.376	-.108	-.528	.601	-.961	.565
	Data Representativeness 2020	.515	.313	.316	1.646	.109	-.121	1.150

a. Dependent Variable: Government Effectiveness 2020

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Total Score 2020	-451.224[b]	-1.088	.285	-.186	7.091E-8
	Technology Sector 2020	-397.934[b]	-.811	.423	-.140	5.145E-8
	Data and Infrastructure 2020	517.730[b]	1.556	.129	.261	1.063E-7

a. Dependent Variable: Government Effectiveness 2020

b. Predictors in the Model: (Constant), Data Representativeness 2020, Digital Capacity 2020, Maturity 2020, Infrastructure 2020, Governance and Ethics 2020, Human Capital 2020, Data Availability 2020, Adaptability 2020, Innovation Capacity 2020, Government 2020

A key interpretation drawn from the data findings discussed above implies that the dependency level of HRM efficiency (expressed through government effectiveness) has declined for the 45 sampled countries over the past four years, from 2020 to 2023. However, because of a lack of data for government effectiveness as of 2024, data assessments were not possible for the same year using the MLR model. Nonetheless, a descriptive statistical analysis was taken into consideration for these variables for 2024, revealing that, on average, most countries on the list are low on the AI readiness maturity scale, with a mean of 38.75, but significantly high for data and infrastructure's representativeness, with a mean of 94.94. With moderate dispersion, the mean for the total score for 2024 stands at 70.75, suggesting that overall, the listed countries are performing fairly well. When focusing on the standard deviation (variability), maturity (SD = 12.15), data and infrastructure (SD = 5.84), and data representatives (SD = 4.86) stand out from the cluster of variables, representing the minimum and maximum values, while the other variables fall into the mid-range dimensions with their corresponding SDs ranging between 10 and 11. While these statistical insights offer valuable inputs about the characteristics of the AI readiness index, interpreting its impacts on HRM efficiency for the year across the different countries will not be possible without the data from the World Bank.

Table 7. Descriptive Statistics for AI Readiness Index for 2024

Descriptive Statistics

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Total Score 2024	45	70.7496	6.25930	.396	.354	-.334	.695
Government 2024	45	78.1540	7.13859	-.903	.354	1.561	.695
Technology Sector 2024	45	52.6538	9.70992	.441	.354	.060	.695
Data and Infrastructure 2024	45	81.4416	5.84469	-.707	.354	.978	.695
Governance and Ethics 2024	45	87.2353	9.15102	-1.420	.354	2.133	.695
Digital Capacity 2024	45	67.6180	10.19110	.155	.354	.574	.695
Adaptability 2024	45	62.2036	10.32283	.417	.354	-.537	.695
Maturity 2024	45	38.7533	12.15121	1.170	.354	2.824	.695
Innovation Capacity 2024	45	63.1242	10.68336	.412	.354	.074	.695
Human Capital 2024	45	56.0836	10.56260	-.284	.354	-.557	.695
Infrastructure 2024	45	65.5504	10.67165	-.350	.354	.129	.695
Data Availability 2024	45	83.8336	7.10476	-.639	.354	.351	.695
Data Representativeness 2024	45	94.9404	4.86247	-1.700	.354	3.131	.695
Valid N (listwise)	45						

Observably, for all the regression models, three common factors were excluded for having a statistically insignificant impact on the dependent variable. These variables were total score (TS_t), technology sector ($Tech.S_t$), and data and infrastructure ($D\&I_t$). Understandably, TS_t reflects the overall AI readiness score, which might be caused by extreme multicollinearity, overlapping the variables grouped under the pillars and dimensions sections. However, when concentrating on the technology sector and data & infrastructure, it can be argued that there could be deeper implications for the exclusion of these variables from the MLR model for each year. For instance, both these factors represent a high-level aggregate that overlaps heavily with its more detailed subcomponents, such as research and development (R&D) intensity and digital adoption, among others. Nonetheless, given the lack of literary information available for these factors linked to HRM efficiency for public sector organizations, the findings do suggest a future need for investigation in this direction.

CONCLUSION

Key Insights

The findings obtained from this research offer valuable insights into the AI readiness index for the public sector in the global context, while aligning the same with the determined research objectives and questions by emphasizing the impacts on HRM efficiency. Infering from both the conceptual or theoretical and statistical findings, it can thus be argued that AI readiness for the public sector depends largely on data governance, human capital, and digital capacity, as well as on the other variables included in the AI readiness framework, which directly contribute to the HRM effectiveness of the public organizations. Based on the data findings, it is undeniable that there is a foundational link between HRM efficiency and AI readiness of the public sector agencies.

Key Arguments

This research was initiated with three fundamental questions, i.e., (i) Do AI readiness affect HRM efficiency within public sector institutions across the globe, (ii) To what extent does HRM efficiency in the public sector institutions affect their AI readiness, and (iii) What common patterns and trends emerge from the AI readiness and HRM efficiency initiatives of public sector institutions across different countries? Based on the data findings, in response to the first research question (i.e., *Do AI readiness affect HRM efficiency within public sector institutions across the globe?*), it can be argued that AI readiness is scored based on ten sub-indices, although the statistical findings suggest that the significance of impacts caused by data representativeness, data availability, human capital, innovation capacity, and digital capacity on government effectiveness is comparatively higher than other variables, collectively and significantly presenting insights into cross-national variation in government effectiveness. A similar argument cannot be presented for the influence of total score, technology sector, and data & infrastructure, which were excluded from the statistical models for having limited to no influence on the dependent variable (i.e., government effectiveness).

As for the second question (i.e., *To what extent does HRM efficiency in the public sector institutions affect their AI readiness?*), the findings suggest that even though the primary models for this research perceived HRM efficiency, through the lens of government effectiveness, theoretical and conceptual assertions indicate a reciprocal relationship between these factors. The findings, however, also suggest that public organizations with mature HRM systems tend to build better data infrastructures while fostering innovation and other performance drivers.

Corresponding to the third question (i.e., *What common patterns and trends emerge from the AI readiness and HRM efficiency initiatives of public sector institutions across different countries?*), the findings reveal that human resources is a key driver for government effectiveness, indicating the strong impacts of AI readiness on HRM efficiency. Precisely, this finding can be interpreted in terms that skill enhancement, digital-literacy training, and talent-management initiatives can offer effective solutions to HRM efficiency challenges. It is also worth emphasizing that these changes or improvements are driven largely through AI integration, further supporting the hypothesis that AI readiness does influence HRM efficiency in public organizations.

POLICY AND MANAGERIAL IMPLICATIONS

From a critical perspective, the findings obtained from this research suggest that initiatives are required by the public sector institutions, irrespective of the global economic status of the country, to invest in strategies to strengthen their corresponding data governance frameworks. This, in turn, will benefit the organizations by expanding their scope to ensure high-quality, representative, and accessible datasets for more effective decision-making for HRM efficiency. These institutions are also required to prioritize digital literacy for their human resources, further taking measures with emphasis on employees' skill enhancement through AI adoption. On the one hand, this will help the institutions to achieve AI readiness maturity and retain HRM efficiency. However, prior to considering these policies and managerial suggestions, the public institutions need to deconstruct overarching AI strategies based on the dimensions of ethics training and infrastructural improvements, to facilitate stronger levels of transparency, accountability, and performance management. From the literary insights obtained in this research, it is also arguable that cultivating partnerships with technology providers and peer governments to co-develop platforms, while sharing best practices and optimizing resources, can be highly beneficial for the public organizations to achieve HRM efficiency through the adaptation of AI technologies.

FUTURE RESEARCH

There were certain literature gaps identified in this research. For instance, there was a lack of evidence providing literary insights into the HRM efficiency practices of public organizations across different countries. Studies supporting arguments about the connections between HRM efficiency and dimensions of the AI readiness index, especially in the public sector context, remain incredibly scarce. A lack of data was also observed when conducting the statistical data evaluation, suggesting that improvements in the data collection and comprehension processes are essential to gain a deeper insight into the research problem. Nonetheless, future initiatives are required to focus specifically on governmental initiatives by emphasizing economic blocs. This will allow for a better insight into the connections between HRM efficiency and AI readiness, while taking into consideration the various economic factors as the control variables. Research is also required to assess the scope for governments across the nations to develop their AI readiness frameworks, in relevance to their barriers or challenges when integrating AI solutions for HRM efficiency.

ACKNOWLEDGEMENTS

This research is funded by the Ministry of Science and Higher Education of the Republic of Kazakhstan (BR24993258).

Ethical Consideration

Author Contribution

I have been involved throughout the process of conceptualization of this research, proceeding further to designing the research methodology, collecting and evaluating the data, and drafting this manuscript.

Conflict of Interest

None observed.

REFERENCES

Amirova, A., Iskendirova S., Daueshova, A., Zhanseitov, A., & Abylasimov, M. (2025). The Impact of Digital HRM Implementation on Public Sector Performance: A Quantitative Analysis of Service Delivery Efficiency. ECONOMICS - Innovative and Economics Research Journal, 13(3), 303-318. https://doi.org/10.2478/eoik-2025-0067

Alami, H., Lehoux, P., Denis, J.-L., Motulsky, A., Petitgand, C., Savoldelli, M., Rouquet, R., Gagnon, M.-P., Roy, D., & Fortin, J.-P. (2020). Organizational readiness for artificial intelligence in health care: insights for decision-making and practice. *Journal of Health Organization and Management*, *35*(1), 106–114. https://doi.org/10.1108/jhom-03-2020-0074

Alsaif, A., & Sabih Aksoy, M. (2023). AI-HRM: Artificial Intelligence in Human Resource Management: A Literature Review. *Journal of Computing and Communication*, *2*(2), 1–7. https://doi.org/10.21608/jocc.2023.307053

Campion, A., Gasco-Hernandez, M., Jankin Mikhaylov, S., & Esteve, M. (2020). Overcoming the Challenges of Collaboratively Adopting Artificial Intelligence in the Public Sector. *Social Science Computer Review*, *40*(2), 089443932097995. https://doi.org/10.1177/0894439320979953

Chatikobo, M. V., & Pasipamire, N. (2024). Readiness to embrace artificial intelligence in information literacy instruction at a Zimbabwean University. *Cogent Education*, *11*(1), 2425209. https://doi.org/10.1080/2331186x.2024.2425209

Cicek, I., & Demir, M. (2015). Efficiency of Human Resource Management: Differences in Actual/Perceptual Performance Evaluations. *Journal of Management, Marketing and Logistics*, *2*(4).

Digital Education Council. (2025). *Ten Dimension AI Readiness Framework*. Digitaleducationcouncil.com. https://www.digitaleducationcouncil.com/post/ten-dimension-ai-readiness-framework

Felemban, H., Sohail, M., & Ruikar, K. (2024). Exploring the Readiness of Organisations to Adopt Artificial Intelligence. *Buildings*, *14*(8), 2460–2460. https://doi.org/10.3390/buildings14082460

Fuentes, P., Hankins, N., Stirling, R., Cirri, G., Grau, G., Rahim, S., & Crampton, E. (2024). Government Al Readiness Index 2024. In *Oxford Insights*. https://oxfordinsights.com/wp-content/uploads/2025/06/2024-Government-AI-Readiness-Index.pdf

Holmstrom, J. (2021). From AI to digital transformation: The AI readiness framework. *Business Horizons*, *65*(3), 329–339. https://doi.org/10.1016/j.bushor.2021.03.006

Ibadildin N., Kenzhin, Zh., Yeshenkulova G., Ismailova R.,Nurguzhina A.,Nassanbekova S., Kadyrova A. ARTIFICIAL INTELLIGENCE IN PROJECT MANAGEMENT: A BIBLIOMETRIC ANALYSIS // Problems and Perspectives in Management, 2025, Volume 23, Issue 2, c.252 - 264. DOI: 10.21511/ppm.23(2).2025.17

Jöhnk, J., Weißert, M., & Wyrtki, K. (2020). Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. *Business & Information Systems Engineering*, *63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Jokinen, S. (2025). *Succeeding in strategic AI adoption: Role of analyzing organizational and technological readiness* [Thesis]. https://osuva.uwasa.fi/server/api/core/bitstreams/0045f1cd-540b-43bf-b140-7875014235c6/content

Kopallé, P., Katsikeas, C., Viglia, G., & Hollebeek, L. D. (2023). Artificial Intelligence, Stakeholder Engagement, and Innovation Value. *Journal of Product Innovation Management*, *Ahead-of-Print*(Ahead-of-Print). https://doi.org/Ahead-of-Print

Lee, A., Shankararaman, V., & Lieh, O. E. (2024). Enhancing citizen service management through AI-enabled systems - a proposed AI readiness framework for the public sector. In Y. Charalabidis, R. Medaglia, & C. van Noordt (Eds.), *Research handbook on public management and artificial intelligence* (pp. 79–96). Edward Elgar Publishing. https://doi.org/10.4337/9781802207347.00014

Madanchian, M., Taherdoost, H., & Mohamed, N. (2023). AI-Based Human Resource Management Tools and Techniques: A Systematic Literature Review. *Procedia Computer Science*, *229*, 367–377. https://doi.org/10.1016/j.procs.2023.12.039

Mohamed, S. A., Mahmoud, M. A., Mahdi, M. N., & Mostafa, S. A. (2022). Improving Efficiency and Effectiveness of Robotic Process Automation in Human Resource Management. *Sustainability*, *14*(7), 3920. https://doi.org/10.3390/su14073920

Muqaddim, N., & Hosain, Md. S. (2021). E-HRM Practices and Operational Efficiency: Evidence from Bangladeshi Garment Industry. *Asian Journal of Economics, Business and Accounting*, *21*(4), 81–96. https://doi.org/10.9734/ajeba/2021/v21i430373

Neumann, O., Guirguis, K., & Steiner, R. (2022). Exploring Artificial Intelligence Adoption in Public organizations: a Comparative Case Study. *Public Management Review*, *26*(1), 1–27. https://doi.org/10.1080/14719037.2022.2048685

Neuwirth, R. J. (2024). The Global Institutional Governance of AI: A Four-Dimensional Perspective. *Int. J. Digit. Law Gov*, *1*(1), 113–153. https://doi.org/10.1515/ijdlg-2024-0004

Nzobonimpa, S., & Savard, J. (2023). Ready but irresponsible? Analysis of the Government Artificial Intelligence Readiness Index. *Policy & Internet*, *15*(3), 397–414. https://doi.org/10.1002/poi3.351

Oxford Insights. (2025). *2024 Government AI Readiness Index*. Oxford Insights. https://oxfordinsights.com/ai-readiness/ai-readiness-index/?#download-reports

Özüdoğru, G., & Durak, H. Y. (2025). Conceptualizing pre-service teachers' artificial intelligence readiness and examining its relationship with various variables: The role of artificial intelligence literacy, digital citizenship, artificial intelligence-enhanced innovation and perceived threats from artificial intelligence. *Information Development*, *41*(3), 916–932. https://doi.org/10.1177/02666669251335657

Phillips, J. (2021). *Human Resource Management: An Applied Approach* (3rd ed.). SAGE Publications.

Russel, S., & Norvig, P. (2021). *Artificial intelligence: A Modern approach* (4th ed.). Prentice Hall.

Saghiri, A. M., Vahidipour, S. M., Jabbarpour, M. R., Sookhak, M., & Forestiero, A. (2022). A Survey of Artificial Intelligence Challenges: Analyzing the Definitions, Relationships, and Evolutions. *Applied Sciences*, *12*(8), 4054. https://doi.org/10.3390/app12084054

Sheikh, H., Prins, C., & Schrijvers, E. (2023). Artificial Intelligence: Definition and Background. *Research for Policy*, 15–41. https://doi.org/10.1007/978-3-031-21448-6_2

Shonhe, L., Min, Q., & Phuti, R. (2024). Government AI readiness in the ESARBICA community: findings from the Oxford Insights AI Readiness Index 2022. *Journal Of The Eastern And Southern Africa Regional Branch of the International Council On Archives*, *43*, 84–101. https://dx.doi.org/10.4314/esarjo.v43i1.6

Socol, A., & Iuga, I. C. (2024). Addressing brain drain and strengthening governance for advancing government readiness in artificial intelligence (AI). *Kybernetes*, *53*(13), 47–71. https://doi.org/10.1108/k-03-2024-0629

Stor, M. (2023). The Effects of Employee Performance Appraisal on the Company Performance Results: The Mediating Role of HRM Outcomes With an Innovative Application of the Efficiency Index. *European Management Studies*, *21*(1), 68–99. https://doi.org/10.7172/1644-9584.99.4

Tehrani, A. N., Ray, S., Roy, S. K., Gruner, R. L., & Appio, F. P. (2024). Decoding AI readiness: An in-depth analysis of key dimensions in multinational corporations. *Technovation*, *131*, 102948–102948. https://doi.org/10.1016/j.technovation.2023.102948

Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, *68*(1), 102588.

World Bank. (2024). *Worldwide Governance Indicators*. World Bank. https://www.worldbank.org/en/publication/worldwide-governance-indicators/interactive-data-access

Zhou, Z., Liu, D., Chen, Z., & Pancho, M. (2025). Government adoption of generative artificial intelligence and ambidextrous innovation. *International Review of Economics & Finance*, *98*, 103953. https://doi.org/10.1016/j.iref.2025.103953