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Determinants of Artificial Intelligence Adoption in Public Sector Human Resource Management: Empirical Evidence from Kazakhstan

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Abstract: *As governments worldwide seek to modernise public administration through digital technologies, understanding the drivers and barriers of Artificial Intelligence (AI) adoption in Human Resource Management (HRM) becomes critically important. This paper investigates determinants of AI adoption among civil servants in Kazakhstan using a large-scale empirical survey of 12,562 public servants conducted in June 2025. We construct and validate composite indices of internal and external HR quality factors (Cronbach's $\alpha = 0.924$ and 0.959, respectively) and estimate three complementary econometric models: an OLS regression explaining HR effectiveness ($R^2 = 0.446$), a binary logistic regression modelling AI adoption (McFadden $R^2 = 0.032$), and a path analysis tracing structural relationships between HR quality, effectiveness perceptions, and AI readiness. Internal HR factors exert a stronger influence on perceived HR effectiveness ($\beta = 0.463$) than external factors ($\beta = 0.227$). Managerial position is the strongest predictor of active AI adoption (OR = 1.609), while tenure negatively relates to AI use (OR = 0.846 per category). Access to modern digital tools positively moderates AI uptake. The paper concludes with policy recommendations for accelerating human-centred AI integration in public-sector HRM.*

Keywords: *artificial intelligence; human resource management; public administration; Kazakhstan; logistic regression; path analysis; digital transformation*

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Introduction

Governments in many parts of the world are under growing pressure to modernise how they manage their workforce. Artificial intelligence has entered this conversation as both a promise and a source of uncertainty. On the one hand, AI-enabled tools have demonstrated tangible potential in automating routine HR tasks, supporting talent selection, and making performance assessments more data-driven (Tambe et al., 2019). On the other hand, most public organisations have been slow to move beyond pilot projects, and the scholarly evidence on what actually determines AI uptake among civil servants remains thin—especially outside Western Europe and North America.

Kazakhstan is an interesting case to examine precisely because it sits at an inflection point. The government launched the Digital Kazakhstan state programme in 2018 and subsequently built the E-Kyzmet platform to digitalise civil service HR procedures, from recruitment to appraisal (Agency for Civil Service Affairs of Kazakhstan, 2023). Yet when we look at actual AI tool usage among public servants, the picture is quite different from the policy ambition. Our survey data show that nearly nine out of ten civil servants either do not use AI at all or have never tried it—even though many say they would like to. Understanding this gap is the central motivation for the present paper.

We draw on a large-scale questionnaire survey administered in June 2025, covering 12,562 civil servants across all regions of Kazakhstan. The dataset is, to our knowledge, one of the largest of its kind for the public sector anywhere. This scale allows us to estimate relatively precise effects for subgroups—by age, gender, tenure, and organisational level—that would be statistically indistinguishable in smaller studies. Beyond describing who uses AI, we build and validate composite indices measuring perceived HR quality and use them in a set of econometric models to explain both HR effectiveness perceptions and AI adoption behaviour.

The structure of the paper is as follows. We first review the relevant bodies of literature on AI in HR, technology acceptance in the public sector, and human capital quality in civil service (Section 1). Section 2 describes the survey design, variable construction, and econometric approach. Section 3 presents and discusses the empirical findings. We conclude with policy implications and a candid assessment of the study's limitations.

1. Literature Review

1.1 Artificial Intelligence in Human Resource Management

Scholarly work on AI in HRM has grown substantially over the past ten to fifteen years, though the volume of empirical studies still lags behind conceptual contributions. Tambe et al. (2019) offer a useful map of the domain, identifying talent acquisition, workforce analytics, learning and development, and performance management as the four areas where algorithmic tools have made the most inroads. The recruitment case has received particular attention: Raghavan et al. (2020) show that NLP-based screening tools can both reduce and amplify demographic bias depending on how they are designed and audited, which has generated ongoing debate about algorithmic fairness in hiring. Learning applications—personalised development pathways built on individual competency data—represent a somewhat less contentious use case, though adoption remains uneven (Baer, 2017; Androniceanu, 2026).

A recurring finding in this literature is that the gap between demonstrated capability and actual organisational uptake is wide. Li et al. (2021) synthesised a large body of survey-based research and found that three factors—perceived ease of use, a sense that the organisation is ready for the technology, and support from direct managers—account for much of the variance in HR technology adoption intentions. What the literature does not resolve cleanly is whether these dynamics look the same in public organisations as in private ones, or whether the employment relationship itself—governed by civil service regulations rather than market contracts—changes how AI tools are perceived and used. Edwards and Edwards (2019) raise this concern indirectly when they document a legitimacy problem: in their data, employees viewed AI-generated HR decisions as less acceptable than identical decisions made by humans, raising the question of whether this reaction is stronger in contexts where formal rules and procedural fairness are especially salient.

1.2 Technology Adoption and HR Quality in the Public Sector

Public administration scholarship has approached technology adoption from a somewhat different angle than the management literature. Wirtz et al. (2019) stress that governments face institutional constraints—accountability requirements, transparency obligations, data protection frameworks—that have no close parallel in private firms, and that these constraints shape not only what AI applications are feasible but also how civil servants and managers perceive them. Fountain's (2001) earlier work on the "virtual state" made a similar point about IT more broadly: bureaucratic structures create powerful path dependencies, and the mere availability of new technology does not by itself change embedded work practices.

Two theoretical frameworks have been particularly influential in empirical studies of technology acceptance in government settings. The Technology Acceptance Model (TAM; Davis, 1989) and its extension UTAUT (Venkatesh et al., 2003) both predict adoption from a combination of perceived usefulness, ease of use, social influence, and what UTAUT calls "facilitating conditions"—access to infrastructure, training, and technical support. Research conducted specifically in public-sector contexts (Alrawabdeh, 2014) tends to find that the usefulness dimension dominates, which is worth bearing in mind when interpreting our results: if civil servants do not see what AI would actually help them do better, the availability of digital infrastructure may not be sufficient to drive uptake.

On the HR quality side, Wright and Pandey (2008) provide evidence that motivational and leadership factors shape how civil servants perceive the effectiveness of their HR systems, while Meijer and Bolívar (2016) connect organisational learning cultures to the success of digital governance initiatives more broadly. Taken together, these threads suggest that how civil servants rate the quality of their own human resources—their competencies, their career prospects, the leadership they work under—may condition their readiness for AI-enabled HR practices. This is the main theoretical claim we investigate empirically.

2. Research Methodology

2.1 Survey Design and Sample

The empirical basis for this paper is a structured questionnaire distributed through the official civil service information system of Kazakhstan between 9 and 11 June 2025. The survey was part of research programme IRN BR24993258 and yielded **12,562 completed responses** from public servants working in organisations across all 17 regions and the three main metropolitan areas. The instrument contained four thematic blocks: socio-demographic profile; perceived quality of HR factors; AI tool use; and attitudes towards the E-Kyzmet digital HR platform.

The respondent profile broadly mirrors the composition of Kazakhstan's civil service. Women make up 61.6 % of the sample. The most represented age group is 36–45 (31.5 %), and educational credentials are concentrated at bachelor's or specialist level (77.6 %). In terms of the employing organisation, 61.9 % work in local executive bodies (regional and district akimats and their sub-units), 24.4 % in territorial departments of ministries and committees, and just 5.5 % in central state bodies—a distribution that reflects the largely decentralised structure of Kazakhstani public administration. The overwhelming majority—four out of five respondents—hold non-managerial, executive positions.

2.2 Variable Construction

The questionnaire asked respondents to rate how strongly a set of factors influenced the quality of human resources in their organisation. Six items described *internal* (individual-level) factors: level of education, professional competency, degree of patriotism and civic commitment, career trajectory prospects, possession of specialised sectoral knowledge, and engagement in continuous professional development. Eight items described *external* (organisational and contextual) factors: comfort of the working environment, quality of leadership and management style, transparency of career advancement, adequacy of social guarantees and working conditions, access to innovative projects, availability of modern digital tools, quality of cross-departmental communication, and fairness of employee performance evaluation. All items used a five-point Likert scale from 1 (minimal influence) to 5 (maximal influence). We averaged scores within each block to form two composite indices.

Demographic variables were coded as ordinals: age in five categories (from ‘under 25’ to ‘over 55’), education in five categories (college graduate through doctoral degree), and tenure in six categories (under three years through over twenty years). We also created binary dummies for female gender, managerial position, and central state body employment. HR effectiveness is the mean of two Likert items: perceived effectiveness of HRM in the civil service as a whole (Q8a) and in the respondent’s own organisation (Q8b). For the logistic regression, AI adoption was dichotomised into active use—those reporting at least weekly use (28.3 % of the sample)—versus non-users and those with only latent interest (71.7 %).

2.3 Econometric Models

Model 1 is an OLS regression in which the HR effectiveness composite is the dependent variable and the two HR quality indices serve as the main regressors alongside eight demographic controls. We report heteroscedasticity-robust standard errors (HC1) throughout. The estimating equation takes the form: $HR\_Eff_i = \beta_0 + \beta_1 \text{ Internal}_i + \beta_2 \text{ External}_i + \beta_3 \text{ Edu}_i + \beta_4 \text{ Age}_i + \beta_5 \text{ Tenure}_i + \beta_6 \text{ Manager}_i + \beta_7 \text{ Female}_i + \beta_8 \text{ Central}_i + \varepsilon_i$.

Model 2 is a binary logistic regression predicting the probability of active AI tool use. In addition to the demographic controls from Model 1, we include the HR effectiveness composite and a single-item measure of perceived access to modern digital tools, since this latter variable captures a facilitating condition that UTAUT theory treats as directly relevant. We report both log-odds coefficients and the corresponding odds ratios to aid interpretation. McFadden’s pseudo-R^2 serves as the overall goodness-of-fit indicator.

Model 3 is a path analysis in standardised metric. Path 1 examines whether HR quality dimensions predict effectiveness perceptions; Path 2 then asks whether those effectiveness perceptions, together with demographic characteristics and digital tool access, predict AI adoption scores (using the full ordinal 0–3 scale rather than the binary indicator). Standardisation allows us to compare effect magnitudes across the two equations. We also report Cronbach’s α for both composite scales; values at or above 0.90 are conventionally regarded as indicating excellent internal consistency (Nunnally, 1978).

3. Research Results and Discussion

3.1 Descriptive Statistics

Table 1 summarises the key variables. A few patterns are worth noting before turning to the regression results. Perceived HR effectiveness is somewhat higher when respondents evaluate their own organisation (mean 4.19) than when they assess the civil service system as a whole (4.08)—a gap that suggests civil servants see their immediate workplace in a somewhat more favourable light than the broader institutional environment, which is a fairly common finding in organisational surveys. Both HR quality indices score well above the scale midpoint: 4.30 on average for internal factors and 4.16 for external ones, indicating that respondents generally view these dimensions as consequential. The AI adoption picture is more mixed. The mean adoption score of 1.08 on the 0–3 ordinal scale translates in practice to a distribution where the largest single category is 'no use and no plans to use' (44.0 %), closely followed by 'interested but not yet using' (another 44.0 %). Only 7.1 % report daily use. This concentration at the lower end of the scale has implications for the regression analysis—it means our binary AI adoption indicator captures a relatively rare behaviour.

Table 1. Descriptive Statistics

Variable	N	Mean	SD	Min	Max
HR Effectiveness – Overall (Q8a)	12,562	4.078	1.047	1	5
HR Effectiveness – Own Organisation (Q8b)	12,562	4.187	1.028	1	5
HR Effectiveness Composite	12,562	4.132	0.972	1	5
Internal HR Quality Index (6 items)	12,562	4.301	0.819	1	5
External HR Quality Index (8 items)	12,562	4.155	0.952	1	5
AI Adoption Score (0–3)	12,562	1.076	0.876	0	3
AI Active Use Binary (1 = yes)	12,562	0.283	0.450	0	1
Education Level (ordinal 1–5)	12,562	1.997	0.415	1	5
Age Group (ordinal 1–5)	12,562	3.086	1.143	1	5
Tenure Group (ordinal 1–6)	12,562	3.776	1.809	1	6
Female (binary)	12,562	0.616	0.487	0	1
Managerial Position (binary)	12,562	0.210	0.407	0	1
Central State Body (binary)	12,562	0.055	0.228	0	1

Authors' processing. N = 12,562. Ordinal variables encoded as described in Section 2.2.

3.2 Scale Reliability

Before interpreting the regression results, it is important to establish whether the two composite scales hold together statistically. Table 2 reports Cronbach's α for each scale. The internal HR quality index (α = 0.924) and the external index (α = 0.959) both comfortably exceed the 0.90 threshold that Nunnally (1978) associated with excellent internal consistency. In practical terms, this means the items in each scale move together closely enough that averaging them into a single composite score is defensible, rather than treating each item as capturing something qualitatively distinct.

Table 2. Scale Reliability – Cronbach's α

Scale	No. Items	Cronbach's α	Interpretation
Internal HR quality factors	6	0.924	Excellent
External HR quality factors	8	0.959	Excellent

Authors' processing. Internal scale: 6 items. External scale: 8 items.

3.3 OLS Regression – Determinants of HR Effectiveness

Table 3 shows the OLS results. Both HR quality dimensions have positive, highly significant coefficients, but they are not equal in magnitude. The internal index—capturing competency, educational level, patriotism, and related individual attributes—has a coefficient of 0.560 ($t = 27.71$, $p < 0.001$), while the external index reaches only 0.239 ($t = 13.25$, $p < 0.001$). This pattern resonates with the OECD (2017) position that civil service effectiveness ultimately rests more on the human capital of individual employees than on organisational structures, though of course both matter. The combined model accounts for 44.6 % of variance in HR effectiveness perceptions, which is a reasonably good fit for a cross-sectional survey with a single-item outcome.

Several demographic patterns are worth discussing. The negative coefficient on education level ($\beta = -0.130$, $p < 0.001$) is perhaps the most counter-intuitive finding in this model. One reading is that more educated civil servants hold higher expectations about HR system quality and are therefore more likely to perceive shortfalls. An alternative reading is that highly educated employees—who may have better labour market options outside the civil service—are more critical of organisational practices generally. Both interpretations are consistent with the data, and distinguishing between them would require follow-up qualitative work. Tenure has a small positive association with effectiveness ratings ($\beta = 0.021$, $p < 0.001$), possibly reflecting the socialisation and familiarity that comes with longer service. Managers rate HR effectiveness somewhat lower than non-managers, as do women, while employees in central state bodies give slightly higher ratings than their counterparts in sub-national bodies.

Table 3. OLS Regression: Determinants of HR Effectiveness Composite

Variable	β	HC1 SE	t-stat	p-value	Sig.
Constant	0.983	0.058	16.84	<0.001	***
Internal HR Quality Index	0.560	0.020	27.71	<0.001	***

Variable	β	HC1 SE	t-stat	p-value	Sig.
External HR Quality Index	0.239	0.018	13.25	<0.001	***
Education Level	−0.130	0.017	−7.47	<0.001	***
Age Group	−0.004	0.008	−0.48	0.635	–
Tenure Group	0.021	0.006	3.77	<0.001	***
Managerial Position	−0.044	0.017	−2.66	0.008	**
Female	−0.086	0.014	−6.14	<0.001	***
Central State Body	0.087	0.027	3.18	0.001	**
$R^2 = 0.446$; Adj. $R^2 = 0.446$; $F = 1{,}263.6$ ($p < 0.001$); $N = 12{,}562$					

Authors' processing. Dependent variable = (Q8a + Q8b) / 2. HC1 robust SE. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

3.4. Binary Logistic Regression – Determinants of AI Adoption

Table 4 turns to the question of who actually uses AI tools. The logistic model reveals several clear gradients in the data. The strongest single predictor is whether the respondent holds a managerial role: managers are 1.61 times more likely to be active AI users compared to those in non-managerial positions (OR = 1.609, z = 9.23, $p < 0.001$). This aligns with Rogers' (2003) diffusion framework, where those with positional authority tend to encounter new technologies earlier and have stronger incentives—or simply more discretion—to experiment with them.

Tenure is perhaps the most striking predictor in terms of policy implications. Each step up the tenure scale reduces the odds of active AI use by roughly 15 % (OR = 0.846, z = −10.28, $p < 0.001$). Since tenure categories span three to five year intervals, a civil servant with 10–15 years of service is substantially less likely to use AI than a colleague who joined within the last three years, even after controlling for age and other factors. This suggests that established work habits and organisational routines—not simply demographic age—are what drive the effect, though age itself also has a separate negative association (OR = 0.917, $p < 0.001$). Both findings indicate that AI adoption in Kazakhstan's civil service is concentrated among a relatively new and more mobile segment of the workforce.

The gender gap is notable: women are about 20 % less likely to be active AI users than men (OR = 0.802, $p < 0.001$). Given that women make up 61.6 % of the sample, this disparity has system-wide significance—it means the majority of the civil service faces above-average barriers to AI adoption. The World Economic Forum (2023) has documented similar gender gaps in digital technology use in many countries, but the Kazakhstani context warrants specific investigation that goes beyond what a survey of this type can provide. Access to modern digital tools, captured here as a single item, carries a small but reliably positive coefficient (OR = 1.104, z = 4.52, $p < 0.001$), which supports the UTAUT argument that facilitating conditions matter. One counterintuitive finding is that higher perceived HR effectiveness is weakly associated with 'lower' AI adoption probability ($OR = 0.922$, $p < 0.001$). We interpret this as a saturation effect: where civil servants judge their HR system to be working well already, they may see less urgency in adopting supplementary digital tools.

Table 4. Binary Logistic Regression: Determinants of AI Adoption

Variable	β	OR	SE	z-stat	p-value	Sig.
Constant	−0.210	0.811	0.156	−1.35	0.178	–
Education Level	0.049	1.050	0.050	0.98	0.328	–
Age Group	−0.087	0.917	0.026	−3.39	<0.001	***
Tenure Group	−0.168	0.846	0.016	−10.28	<0.001	***
Managerial Position	0.476	1.609	0.052	9.23	<0.001	***
Female	−0.221	0.802	0.042	−5.20	<0.001	***
Central State Body	0.075	1.078	0.088	0.85	0.395	–
HR Effectiveness Composite	−0.081	0.922	0.024	−3.45	<0.001	***
Digital Tools Access	0.099	1.104	0.022	4.52	<0.001	***
McFadden $R^2 = 0.032$; Accuracy = 71.9 %; N = 12,562						

Authors' processing. Dependent variable = 1 if respondent uses AI at least weekly; 0 otherwise. OR = odds ratio. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

3.5 Path Analysis

Table 5 brings the two stages together in a standardised path framework, allowing us to compare effect sizes directly. Path 1 confirms, now in standardised metric, that internal HR factors ($\beta = 0.463$) outweigh external ones ($\beta = 0.227$) in shaping HR effectiveness perceptions—the ratio is roughly 2:1, which is consistent across all three model specifications and appears to be a robust feature of the data rather than a modelling artefact.

Path 2 examines AI adoption. The structural effect running from HR effectiveness to AI adoption is negative and statistically significant ($\beta = -0.033$, $p = 0.003$), though very small in magnitude. This finding, which replicates the logistic regression result in a different modelling framework, reinforces the saturation interpretation above. What stands out more starkly in the standardised coefficients is the gender effect: being female is associated with a 0.095 standard deviation reduction in AI adoption—the single largest predictor in Path 2 in absolute terms, ahead of both age ($\beta = -0.054$) and digital tool access ($\beta = 0.034$). The R^2 for Path 2 is only 0.015, which is modest but not surprising: whether or not a civil servant uses AI tools is likely driven substantially by motivational and contextual factors—personal curiosity, peer influence, task requirements—that a short survey on HR quality was not designed to capture.

Table 5. Path Analysis: Standardised Coefficients

Path / Variable	Std. β	t / z	p-value	Sig.
Path 1 – Dependent variable: HR Effectiveness ($R^2 = 0.440$)				
Internal HR Quality Index	0.463	27.60	<0.001	***
External HR Quality Index	0.227	13.02	<0.001	***
Path 2 – Dependent variable: AI Adoption Score ($R^2 = 0.015$)				
HR Effectiveness Composite	−0.033	−2.98	0.003	**
Age Group	−0.054	−5.93	<0.001	***
Education Level	0.010	1.09	0.277	–
Digital Tools Access	0.034	3.32	<0.001	***
Female	−0.095	−10.37	<0.001	***

Authors' processing. All variables standardised (z-scores). *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

4. Conclusions

We set out to understand what drives AI adoption among civil servants in Kazakhstan, using what we believe is the largest survey dataset on this question yet assembled for a post-Soviet public administration. The main contribution is not any single finding but the combination of scale, validated measurement, and triangulated estimation strategy. Several substantive conclusions follow.

On HR effectiveness, the dominant story is that individual-level factors—competency, specialised knowledge, civic commitment, and a disposition towards continuous learning—matter roughly twice as much as organisational and contextual factors in shaping how civil servants evaluate their HR system. This is not a trivial result. It suggests that training programmes and merit-based career development will buy more in terms of perceived HR quality than administrative restructuring or changes to working conditions on their own. That said, the external factors are also significant, and the finding that managers rate HR effectiveness lower than non-managers is a signal worth investigating further: it may reflect sharper awareness of gaps in the system, or something about how managerial roles are structured.

On AI adoption, three patterns stand out. Managers are considerably more likely to use AI tools. Longer-serving employees are considerably less likely—and this effect holds even after controlling for age, which suggests it is not simply about generational attitudes but about embedded habits and task definitions accumulated over years of service. Women are systematically less likely to adopt AI, by a margin large enough to have real implications for who benefits from productivity gains if AI does become more widespread in the civil service. Addressing each of these gradients requires different policy responses: it is not enough to deploy AI systems and assume diffusion will take care of itself.

We should be transparent about what this study cannot establish. The data are cross-sectional, so we cannot rule out that the relationships we observe reflect reverse causation or confounding by unmeasured individual characteristics. The survey measured AI adoption via a single self-report item, which tells us nothing about how intensively or effectively tools are used when they are used. And the low R^2 in the AI adoption equation is a reminder that a great deal of the variation in uptake behaviour lies in motivational and social factors that a questionnaire focused on HR quality cannot capture. Future work using longitudinal data, linked administrative records, or qualitative case studies would help address each of these limitations. In the meantime, the present findings offer a useful empirical baseline for policymakers working on AI integration strategies in Kazakhstan and comparable settings.

Conflict of Interest Statement

The authors report no conflicts of interest of any kind in connection with the research presented in this article.

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