

ECOSYSTEM AND HUMAN-CENTRIC HRM IN KAZAKHSTAN'S CIVIL SERVICE

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ABSTRACT

Human-centric and ecosystem-based approaches to human resource management (HRM) have gained increasing attention in public administration reform, particularly in transitional states. However, large-scale empirical evidence remains limited, especially in Central Asia. This study investigates the individual and institutional determinants of perceived HRM quality in Kazakhstan's civil service and examines why the adoption of artificial intelligence (AI) remains constrained. Using a nationally representative survey of 12,562 civil servants conducted in June 2025, the analysis employs ordinary least squares regression with heteroskedasticity-robust standard errors and binary logistic regression. The findings show that perceived HRM quality is driven primarily by access to education and training, public service motivation (patriotism), and participation in innovative projects, with the model explaining 39.8% of the variance. In contrast, AI adoption is influenced more by organisational position and institutional access than by individual motivation. Managers are substantially more likely to use AI tools, whereas women and longer-tenured civil servants exhibit lower adoption rates. Notably, 44% of respondents report wanting to use AI but lacking access, pointing to a significant implementation gap. The study makes three principal contributions. First, it provides the first large-scale empirical assessment of the ecosystem-based and human-centric HRM framework in a post-Soviet context. Second, it demonstrates that the AI adoption gap is primarily structural rather than motivational. Third, it translates these empirical findings into actionable policy recommendations. The results suggest that narrowing the AI aspiration gap and creating more transparent and accessible career pathways should constitute key priorities for civil service reform, requiring coordinated system-level interventions rather than isolated organisational initiatives.

Keywords: *ecosystem approach, human resource management, public service, human-centric principle, Kazakhstan, civil servants, artificial intelligence, public service motivation, digital transformation*

1. INTRODUCTION

Kazakhstan's civil service has undergone substantial transformation since the country gained independence. Educational attainment among civil servants has risen considerably, with more than 77% of officials now holding at least a bachelor's degree, while successive reforms have

accelerated the digitalisation of public services. Although these developments represent significant institutional achievements, they do not necessarily imply corresponding improvements in the quality of human resource management (HRM) or workforce development. Despite the central role of civil servants in public sector performance, there remains limited large-scale empirical evidence on the factors shaping HRM quality in post-Soviet administrations. This study addresses that gap by examining the individual and institutional determinants of perceived HRM quality in Kazakhstan's civil service.

The analysis is grounded in the ecosystem approach to HRM, which conceptualises public organisations as interconnected socio-technical systems rather than traditional hierarchical bureaucracies. Within this perspective, civil servants, managers, HR departments, training institutions, and digital platforms continuously interact and evolve within a shared institutional environment (Bommert, 2010; Torfing et al., 2020; Hunady et al., 2025). Complementing this perspective, the human-centric approach introduces a normative dimension by viewing civil servants not merely as instruments of policy implementation but as individuals whose professional development possesses intrinsic value alongside its contribution to organisational performance (Sen, 1999; UNDP, 2021). This distinction is particularly relevant in post-Soviet administrative systems, where bureaucratic traditions historically prioritised procedural compliance over professional autonomy. Elements of this legacy continue to shape workplace experiences in Kazakhstan, as demonstrated by the descriptive evidence presented later in the paper.

The empirical analysis draws on a nationally distributed survey of 12,562 Kazakhstani civil servants conducted in June 2025 under the national research programme IRN BR24993258 and administered through the Academy of Public Administration. The survey covers all 17 oblasts and the three cities of republican significance, including respondents from central government agencies, territorial ministry departments, and local executive bodies. Four research questions guide the study. First, which individual and organisational factors most strongly influence civil servants' perceptions of HRM quality? Second, how do these perceptions differ according to organisational position, tenure, and level of government? Third, what distinguishes civil servants who actively use artificial intelligence (AI) tools from those who do not? Finally, which HRM challenges do practitioners themselves consider the highest priorities for future reform?

This study makes three principal contributions. First, it provides the first large-scale empirical assessment of the combined ecosystem and human-centric HRM framework within a post-Soviet civil service, transforming what has largely remained a conceptual framework into an empirically testable model. Second, it demonstrates that the limited adoption of AI tools reflects primarily structural and organisational constraints rather than a lack of individual motivation, thereby redirecting attention towards institutional barriers to digital transformation. Third, it translates these empirical findings into practical, multi-level policy recommendations for civil service reform. Although the analysis focuses on Kazakhstan, its implications extend beyond a single national context. Many countries across Central Asia, the South Caucasus, and post-communist Eastern Europe continue to face comparable challenges arising from Soviet administrative legacies, uneven digital transformation, and growing public expectations regarding service quality. While the findings cannot be directly generalised to other settings, they provide useful empirical benchmarks and methodological guidance for researchers and policymakers working in similar institutional environments.

1. 1. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

1. 1. 1. ECOSYSTEM HRM: FROM METAPHOR TO AN ANALYTICAL FRAMEWORK

The ecosystem concept was originally introduced by [Moore \(1993\)](#), who argued that competitive advantage emerges not from individual organisations but from networks of interdependent actors operating within broader systems. The concept was subsequently adopted in public administration to explain collaborative governance arrangements ([Ansell & Gash, 2008](#)) and, more recently, the institutional foundations of digital government transformation ([Mergel et al., 2018](#)). Applied to HRM, the ecosystem perspective argues that civil service quality is produced through the interaction of multiple mutually reinforcing components rather than through any single policy instrument. Individual competencies, leadership practices, organisational systems, training provision, and institutional conditions jointly shape workforce development and organisational performance.

[Kuperus and Rode \(2016\)](#) operationalise this perspective through a four-level framework comprising individual capabilities and motivation, supervisory and team relationships, organisational HR systems including performance management and career development—and the wider institutional environment encompassing training provision and digital infrastructure. The principal contribution of this framework lies in recognising the interdependence between these levels. Improvements introduced at one level are unlikely to achieve their intended outcomes unless complementary reforms occur across the wider system. This helps explain why isolated HR reforms, such as introducing competency frameworks without corresponding changes to promotion systems, frequently produce disappointing results.

The human-centric perspective complements the ecosystem framework by emphasising that the development of civil servants constitutes an objective rather than merely a means of improving organisational performance. This principle draws directly on [Sen's \(1999\)](#) capability approach and [Nussbaum's \(2011\)](#) human development framework, both of which emphasise expanding individuals' opportunities to develop their capabilities. Consequently, the central analytical question extends beyond identifying the factors that improve current job performance to understanding the institutional conditions that enable long-term professional development throughout a civil servant's career.

1. 1. 2. INTERNAL AND EXTERNAL DETERMINANTS OF HRM QUALITY

Research on public sector performance traditionally distinguishes between individual (internal) and organisational (external) determinants of employee performance. Among internal factors, educational attainment and professional competencies consistently emerge as key predictors of effectiveness ([Boxall & Purcell, 2011](#)). Equally important is public service motivation (PSM), defined as an intrinsic commitment to serving the public interest through civic responsibility, public values, and national identification. A substantial body of international evidence demonstrates that PSM positively influences employee performance, organisational commitment, and job satisfaction ([Perry, 1996](#); [Vandenabeele, 2007](#); [Van Loon et al., 2015](#)). [Perry and Wise \(1990\)](#) originally identified patriotism as one component of public service motivation, a dimension that may hold particular significance in post-Soviet contexts where public employment remains closely linked to nation-building and state legitimacy.

Among external determinants, leadership quality and management practices have received the greatest empirical attention, reflecting the central role of supervisory relationships in shaping employees' day-to-day experiences ([Vandenabeele et al., 2004](#); [OECD, 2019](#)). Career transparency has likewise become increasingly important as merit-based promotion systems expand, although considerable gaps often remain between formal procedures and actual prac-

tice. More recently, access to digital technologies has emerged as an additional determinant of HRM quality. Accelerated digitalisation following the COVID-19 pandemic transformed digital infrastructure from a technical resource into a fundamental component of everyday administrative work, particularly across Central Asia, where access to digital tools increasingly influences both organisational performance and employee experience (Zhanbyrbayeva et al., 2022; Amirova et al., 2025).

1. 1. 3. AI AND DIGITAL TOOLS IN CIVIL SERVICE HRM

Artificial intelligence has become increasingly integrated into HRM through applications such as automated recruitment, personalised training recommendations, workforce analytics, and performance management (Dwivedi et al., 2021; Tambe et al., 2019; European Commission, 2025). Recent research demonstrates the expanding role of AI in HRM across emerging economies. For example, Alayed and Awamleh (2025) show that AI improves HR practices through business intelligence systems in Jordanian firms, AIOqaily et al. (2025) find that AI adoption reduces employee burnout by improving work–life balance, and Thangaraju and Palani (2025) demonstrate that AI-enabled sustainable HRM enhances creative performance within India’s information technology sector. Despite these advances, existing research remains heavily concentrated on private-sector organisations.

Evidence from public administration remains comparatively limited, where AI adoption is constrained not only by technology but also by administrative hierarchies, procurement regulations, accountability requirements, and managerial approval. These institutional constraints are particularly evident in post-Soviet administrations. Wirtz et al. (2019) argue that slow AI adoption primarily reflects risk-averse organisational cultures, underdeveloped data governance, and shortages of digital skills rather than technological limitations or financial costs.

Kazakhstan’s E-Kyzmet platform, which integrates recruitment, performance evaluation, and career management within a unified digital HR system, represents a promising foundation for AI-supported HRM. However, despite its strategic importance, little empirical evidence exists regarding how civil servants use the system or perceive its value in everyday administrative practice. This study provides the first large-scale empirical assessment of these issues.

2. MATERIALS AND METHODS

2. 1. SURVEY DESIGN AND DATA COLLECTION

The survey instrument was developed by the research team at the Academy of Public Administration under the President of the Republic of Kazakhstan within the national research programme “*Ecosystem Approach to Human Resource Management in Public Service Based on the Human-Centric Principle with Digital Tools*” (IRN BR24993258). The questionnaire comprised fourteen substantive items organised into five thematic sections: (1) socio-demographic characteristics; (2) overall perceptions of HRM quality measured on a five-point Likert scale; (3) six internal (individual-level) determinants of HRM quality measured on five-point Likert scales; (4) eight external (organisational and institutional) determinants of HRM quality measured using the same scale; and (5) indicators of digital readiness and AI use. The questionnaire was administered in both Kazakh and Russian and distributed through Google Forms between 9 and 11 June 2025 via the official communication channels of the Agency for Civil Service Affairs (ACSA) and all regional *akimats*.

A total of 12,562 valid responses were collected. At the time of the survey, Kazakhstan’s civil service employed approximately 95,000 officials (ACSA, 2024), resulting in a coverage rate of 13.2%, substantially exceeding the response rates typically considered adequate for large-

scale organisational surveys. The principal limitation of the sampling strategy is its reliance on voluntary participation through official institutional channels, which may have led to the overrepresentation of more engaged or institutionally committed civil servants. This potential source of bias is discussed further in Section 5.4. Nevertheless, the sample exhibits broad geographical and organisational coverage, including respondents from all 17 oblasts, the three cities of republican significance, and every level of the governmental hierarchy.

Two potential sources of measurement bias require explicit consideration. First, because all variables were collected through a single self-administered questionnaire, the results may be affected by common method variance. Second, responses to sensitive constructs, particularly perceived HRM quality and patriotism as an indicator of public service motivation may be influenced by social desirability bias within a hierarchical public administration context. To minimise these risks, several procedural safeguards recommended by Podsakoff et al. (2003) were incorporated into the survey design. Participation was entirely voluntary and anonymous, with no personal identifiers, personnel numbers, or workplace-specific information collected. This design reduced incentives for respondents to provide institutionally favourable answers. Furthermore, predictor variables (internal and external HRM factors) and outcome variables (overall HRM quality) were presented in separate questionnaire sections under neutral headings to reduce implicit consistency effects, while the bilingual wording was carefully designed to avoid leading or suggestive language.

As an additional empirical check, the regression models reported below explain approximately 39.8% of the variation in perceived HRM quality, leaving around 60% unexplained. This pattern is inconsistent with the presence of a dominant common method factor, which would typically inflate explained variance substantially. Nevertheless, the possibility of residual social desirability bias cannot be entirely excluded and is therefore acknowledged as a limitation in Section 5.4.

2. 2. SAMPLE PROFILE

Table 1 presents the socio-demographic characteristics of the respondents. Women constitute 61.6% of the sample, closely matching the gender composition of Kazakhstan's civil service reported in administrative statistics (ACSA, 2021). The largest age group comprises respondents aged 36–45 years (31.5%), followed by those aged 26–35 years (26.4%). Most respondents hold a bachelor's or specialist degree (77.6%), reflecting the highly educated nature of the civil service workforce.

Executive (non-managerial) employees account for 79.0% of the sample, while officials employed in local executive bodies, including village, district, and oblast *akimats*, represent 61.9% of all respondents, making local government the most represented level of administration.

3. RESULTS

3. 1. HOW CIVIL SERVANTS RATE HRM QUALITY

In Model 1, the dependent variable is respondents' evaluation of overall HRM quality in Kazakhstan's civil service, measured on a 1–5 scale. The explanatory variables include all six internal and all eight external HRM quality factors, each assessed on the same 1–5 scale, alongside controls for gender, age group, education level, civil-service tenure, position level, and governance tier. Age is measured using five ordinal categories, education using four categories, tenure using six categories, position level is coded as a managerial dummy variable, and governance tier distinguishes between local, territorial, and central government bodies. The model is estimated using ordinary least squares with HC1 heteroskedasticity-robust standard errors, following White (1980). Treating a five-point Likert scale as continuous is common in

large-scale survey research and is unlikely to pose practical concerns given the large sample size (Sullivan & Artino, 2013).

Model 2 examines which civil servants regularly use AI tools, defined as daily or weekly use. The dependent variable is binary, with regular users coded as 1 and all other respondents coded as 0. The model is estimated using logistic regression with a Newton-Raphson maximum-likelihood procedure. The predictors include competency level, continuous professional development, career trajectory, access to digital tools, participation in innovation projects, and the same demographic controls used in Model 1. In addition, a Pearson correlation matrix is examined for all 14 HRM quality factors. Complete-case analysis produces a final sample of $N = 10,826$ for Model 1, corresponding to 86.2% retention, and $N = 11,735$ for Model 2, corresponding to 93.4% retention.

3. 2. INTERNAL FACTORS: WHAT MATTERS AT THE INDIVIDUAL LEVEL

Six internal factors were assessed on a 1–5 scale (Table 2). Competency level and patriotism or commitment to public service recorded the highest mean scores ($M = 4.40$ for both), a pattern that aligns closely with the public service motivation literature discussed in Section 2. Education level followed closely ($M = 4.38$), while continuous professional development ($M = 4.29$) and specialised sectoral knowledge ($M = 4.28$) occupied the middle of the distribution. Career trajectory received the lowest rating ($M = 4.06$) and displayed the greatest variation ($SD = 1.11$), suggesting notable disagreement among respondents about the clarity and accessibility of promotion pathways within the civil service.

Managers rated all six internal factors more positively than executive staff. The largest difference was observed for career trajectory, with managers reporting a mean score of 4.22 compared with 4.01 among executive employees. This pattern is unsurprising, since officials who have already advanced into managerial roles are more likely to view the promotion system favourably. More important, however, is the comparatively lower score among executive staff, who represent nearly 80% of the sample and perform much of the civil service's operational work. Their more cautious assessment of career prospects points to a potential weakness in internal mobility and deserves close policy attention.

3. 3. EXTERNAL FACTORS: THE ORGANISATIONAL AND INSTITUTIONAL LAYER

Eight external factors were measured using the same 1-5 scale (Table 3). Leadership and management style received the highest rating ($M = 4.28$, $SD = 0.99$), followed closely by comfortable working environment ($M = 4.27$) and transparency of performance evaluation ($M = 4.22$). Career-advancement transparency ($M = 4.14$), access to digital tools ($M = 4.12$), social guarantees ($M = 4.11$), and inter-departmental communication ($M = 4.10$) formed a closely grouped middle tier. Participation in innovative and strategic projects ranked lowest and was the only external factor with a mean below 4.00 ($M = 3.99$). Its relatively high standard deviation ($SD = 1.14$) also indicates substantial variation in respondents' experiences.

The low ranking of innovation participation is particularly important. Unlike other external factors, the difference between managers and executive staff is smallest for this item (4.07 versus 3.97), suggesting that limited involvement in innovative and strategic projects is not simply a problem of hierarchical position. Rather, it appears to reflect a broader system-level constraint. Civil servants across organisational levels report limited opportunities to participate in meaningful strategic or creative work. For a public administration pursuing an ambitious modernisation agenda, this points to a clear mismatch between reform objectives and employees' reported workplace experience.

3. 4. OLS REGRESSION: WHAT PREDICTS HRM QUALITY PERCEPTIONS?

OLS regression results are reported in Table 4. The full specification, estimated using $N = 10,826$ observations, explains a substantial proportion of the variation in perceived HRM quality ($R^2 = 0.398$, Adjusted $R^2 = 0.397$; $F(20, 10,805) = 357.3$, $p < 0.001$). Explaining approximately 40% of the variance in a cross-sectional attitudinal survey represents a relatively strong model fit. At the same time, the results indicate that around 60% of the variation in HRM quality perceptions is attributable to factors not captured by the individual- and organisational-level variables included in the analysis, an issue discussed further in Sections 5.4 and 5.5.

Among the internal predictors, respondents' assessment of education and training opportunities emerges as the strongest determinant of perceived HRM quality ($\beta = 0.187$, $SE = 0.021$, $p < 0.001$). Public service motivation, measured through patriotism, is the second most influential predictor ($\beta = 0.122$, $p < 0.001$), followed by competency level ($\beta = 0.108$, $p < 0.001$) and perceptions of career trajectory ($\beta = 0.067$, $p < 0.001$). By contrast, specialised knowledge and continuous professional development do not remain statistically significant after controlling for the full set of covariates. The most plausible explanation is multicollinearity, as both variables are highly correlated with the broader education and competency measures ($r = 0.798$). Consequently, their unique effects cannot be reliably separated from these closely related constructs, although this should not be interpreted as evidence that they lack practical importance.

Among the external determinants, participation in innovation projects is the strongest predictor of perceived HRM quality ($\beta = 0.097$, $p < 0.001$), followed by leadership and management style ($\beta = 0.083$, $p < 0.001$), transparency of performance evaluation ($\beta = 0.070$, $p < 0.001$), and the quality of the working environment ($\beta = 0.066$, $p < 0.001$). In contrast, career advancement transparency, social guarantees, access to digital tools, and inter-departmental communication do not retain statistical significance in the fully adjusted model, despite exhibiting moderate positive bivariate correlations with HRM quality ($r = 0.48$ – 0.53). This pattern suggests that these variables are better interpreted as indicators of broader organisational quality rather than as independent determinants of perceived HRM performance.

Among the control variables, two findings are particularly noteworthy. Female respondents report slightly lower HRM quality ratings than their male counterparts ($\beta = -0.082$, $p < 0.001$). In addition, respondents with higher levels of education tend to evaluate HRM quality less favourably ($\beta = -0.148$, $p < 0.001$), a pattern frequently observed in studies of institutional quality and commonly interpreted as reflecting higher expectations and more critical evaluative standards among better-educated individuals. Civil-service tenure is positively, although only modestly, associated with HRM quality perceptions ($\beta = 0.020$, $p < 0.01$). Interestingly, managers provide slightly lower evaluations of HRM quality than executive staff ($\beta = -0.063$, $p < 0.01$), which may reflect greater awareness of organisational shortcomings arising from their closer involvement in management and implementation processes.

3. 5. BINARY LOGIT: WHO USES AI TOOLS?

Just over one-quarter of respondents (28.3%) report using AI tools on a regular basis, including 7.1% who use them daily and 21.2% who use them at least weekly. An additional 44.0% do not currently use AI but express a desire to do so, while the remaining 27.7% neither use AI tools nor intend to adopt them. The results of the logistic regression are presented in Table 5 ($N = 11,735$, McFadden $R^2 = 0.032$, classification accuracy = 71.3%).

Managerial position emerges as the strongest predictor of AI adoption. Managers are 64.7% more likely than executive staff to be regular AI users ($\beta = 0.499$, $OR = 1.647$, $p < 0.001$), suggesting that access to AI technologies is strongly associated with organisational position. This pattern is consistent with differences in software availability, job responsibilities, and

organisational incentives, as managerial roles often involve greater access to digital tools and stronger expectations regarding productivity and innovation.

Civil-service tenure exhibits the opposite relationship. Each additional tenure category, corresponding to approximately three to five additional years of service, is associated with a 15.6% reduction in the odds of regular AI use ($\beta = -0.170$, $OR = 0.844$, $p < 0.001$). This finding indicates that longer-serving officials are less likely to incorporate AI into their daily work, potentially reflecting established work routines developed before the widespread availability of AI technologies.

Gender differences are also evident. Women are significantly less likely than men to report regular AI use ($OR = 0.793$, $p < 0.001$). This finding is particularly relevant given that women constitute 61.6% of Kazakhstan's civil service workforce and is consistent with previous research documenting gender disparities in digital technology adoption within the public sector. Age exerts an additional independent effect beyond tenure, with older respondents displaying lower rates of AI adoption ($\beta = -0.083$ per category, $p < 0.01$).

Finally, access to workplace digital technologies increases the likelihood of AI adoption by 8.4% ($OR = 1.084$, $p < 0.05$). Although the estimated effect is relatively modest, its direction underscores the importance of organisational infrastructure in shaping individual technology use. Civil servants working in digitally equipped environments are more likely to integrate AI tools into their routine work practices, highlighting the role of institutional capacity in supporting digital transformation.

3. 6. WHAT CIVIL SERVANTS ACTUALLY WANT

Two descriptive findings are worth highlighting before turning to interpretation. First, respondents were asked how they currently use AI or how they would most like to use it. The most frequently mentioned use was text composition, including drafting annotations, formal applications, and correspondence (1,680 mentions), followed closely by language translation (1,676) and large-dataset processing (1,269). Simplifying tasks within **E-Kyzmet** ranked fourth (787 mentions), ahead of generating individual professional-development plans (693). These preferences are notably practical and task oriented. Civil servants do not primarily view AI as a tool for strategic decision-making or governance reform; rather, they see it as a means of reducing the administrative burden that occupies much of their daily work.

Second, respondents identified their broader HRM development priorities. Training and professional development emerged as the most frequently selected priority, chosen by 6,957 respondents, or 55.4% of the sample. Performance assessment and motivation ranked second at 47.4%. Employee engagement and satisfaction, evaluation-system improvement, and career planning each attracted support from roughly 17-21% of respondents. Particularly striking is the strong support for establishing dedicated university preparation programmes for future civil servants: 81.0% of respondents endorsed this proposal, while only 5.6% opposed it. Such a high level of practitioner consensus is rare in public-sector reform, and the finding provides a clear mandate for institutional action on pre-service civil service education.

4. DISCUSSION

4. 1. READING THE REGRESSION THROUGH AN ECOSYSTEM LENS

The regression results are broadly consistent with the ecosystem model developed in Section 2, although they also reveal several unexpected patterns. The prominence of education level and patriotism among the internal predictors aligns with the public service motivation literature (Perry, 1996; Boxall & Purcell, 2011) and supports the theoretical emphasis on foundational professional attributes. More surprising is the lack of independent significance for con-

tinuous professional development and specialised knowledge once education and competency are included in the model. Statistically, this is explained by collinearity ($r = 0.798$), but it does not imply that these dimensions are unimportant in practice. Respondents ranked them fourth and fifth in the descriptive results, suggesting that their influence is absorbed into broader overlapping constructs rather than absent from the HRM ecosystem.

The most notable result is the strength of innovation-project participation ($\beta = 0.097$) as an external predictor of perceived HRM quality, exceeding leadership style ($\beta = 0.083$) and all other organisational factors. Torfing et al. (2020) argue that public-sector innovation depends on meaningful practitioner involvement rather than top-down instruction alone. When civil servants participate as co-producers of change rather than passive recipients of reform directives, their working environment is likely to be experienced differently. The findings support this view: respondents who report involvement in strategic and creative work also report higher overall HRM quality. Yet this result is also concerning, since innovation participation received the lowest rating among all 14 survey items. The gap between its importance and its availability identifies a clear priority for reform.

The non-significance of digital-tool access in Model 1 should not be interpreted as evidence against Kazakhstan's broader e-government agenda. Rather, it suggests that access to digital tools alone is insufficient to improve perceptions of HRM quality. Digitalisation must be accompanied by changes in work organisation, management practices, and institutional routines. Without these complementary conditions, technology may improve the appearance of modernisation without substantially improving its practical substance.

4. 2. THE AI ASPIRATION GAP AND WHAT TO DO ABOUT IT

The finding that 44% of respondents want to use AI but currently cannot is arguably the most policy-relevant result of the study. Importantly, this gap appears to reflect organisational constraints rather than a lack of individual motivation. Consistent with Wirtz et al. (2019), who argue that successful AI adoption in the public sector depends primarily on targeted training and access to officially supported technologies rather than awareness campaigns, the evidence suggests that the principal barriers are structural. Civil servants already express demand for AI tools, but access to appropriate platforms, formal training, and clear managerial approval remains limited. Moreover, the AI applications most frequently requested text generation, language translation and data processing are already available through mature commercial technologies. The principal obstacles therefore lie in procurement, organisational access and institutional support rather than technological availability.

The logistic regression reinforces this interpretation. Organisational position is the strongest predictor of AI adoption, with managers substantially more likely than executive staff to use AI tools regularly. Neither education nor technical competence exerts a comparable influence, indicating that access and managerial authorisation are more important than individual capability. In practice, routine AI use requires three basic conditions: access to approved software, supervisory support for its use, and sufficient training to apply it effectively. None of these requirements entails substantial financial investment, suggesting that meaningful improvements could be achieved through relatively low-cost organisational reforms.

The analysis also identifies two groups with significantly lower levels of AI adoption: women (OR = 0.793) and longer-serving civil servants (OR = 0.844 per tenure category). These findings carry considerable practical importance because women constitute 61.6% of Kazakhstan's civil service, while 25.7% of employees have served for more than twenty years. Consequently, these groups represent a substantial share of the workforce and should be central to future digital transformation initiatives.

Although the cross-sectional design does not permit causal inference, several plausible mechanisms may explain these disparities. The lower adoption rate among women is unlikely to reflect differences in ability. Instead, it may arise from their greater concentration in administrative and clerical positions characterised by narrower task discretion, combined with heavier domestic responsibilities that limit opportunities for independent upskilling and comparatively weaker access to the informal professional networks through which digital practices often spread. Similarly, longer-serving officials may be less inclined to adopt AI because established work routines increase the perceived costs of changing familiar practices, while AI-related competencies have rarely been incorporated into the in-service training received by this cohort. These observations point directly towards the qualitative research agenda proposed in Section 5.5 while also informing practical policy design. Rather than relying on broad awareness campaigns, efforts to reduce the aspiration-access gap should focus on role-specific, hands-on AI training delivered through E-Kyzmet during working hours, the appointment of digital champions within organisational units to encourage peer learning, explicit managerial approval for the use of authorised AI applications, and the routine provision of AI-enabled software on standard workplace devices. Because the principal constraints relate to organisational access and institutional permission rather than employee motivation, such interventions are likely to be both relatively inexpensive and highly scalable.

4. 3. ON THE CAREER-TRAJECTORY PROBLEM

Career trajectory received the lowest mean rating among the internal HRM factors, yet it remained a statistically significant predictor of perceived HRM quality in the regression analysis ($\beta = 0.067$). The combination of relatively low satisfaction and a meaningful positive association with overall HRM quality identifies career development as an important area for policy intervention. The differences across organisational levels reinforce this conclusion. Managers reported more favourable perceptions of career trajectory than executive staff (4.22 versus 4.01), suggesting that opportunities for advancement are viewed differently depending on position within the hierarchy. Given that executive employees account for nearly 80% of respondents and perform most operational functions, their comparatively lower confidence in career progression is particularly important. As this group represents the primary pool of future managerial talent, perceptions of limited or unclear advancement opportunities may weaken leadership succession over time. International evidence indicates that transparent merit-based promotion systems and structured mentoring programmes can strengthen career development and improve employee engagement (Vandenabeele et al., 2004; OECD, 2019), making them logical priorities for future civil service reform.

4. 4. LIMITATIONS

Five limitations should be explicitly acknowledged. First, distribution through official ACSA and *akimat* channels may have introduced self-selection bias, as respondents were likely to be more engaged with institutional communication than non-respondents. As a result, perceived HRM quality may be somewhat overstated. Second, all variables were collected through a single self-reported questionnaire, creating potential risks of common-method variance and social-desirability bias. These concerns are particularly relevant for sensitive items such as patriotism and perceived HRM quality, despite the procedural safeguards described in Section 3.1. Third, the data are cross-sectional and were collected within a single month, June 2025, meaning that causal direction cannot be established. For example, the positive association between innovation participation and HRM quality perceptions may reflect reverse causality, whereby more motivated officials are both more likely to participate in innovative projects and

more likely to evaluate their workplace favourably. Fourth, the OLS model explains 39.8% of the variance, leaving approximately 60% unexplained. This indicates that unobserved institution-level factors, such as regional budget constraints, organisational subcultures, leadership turnover, and differences in baseline digital literacy, may also shape HRM quality perceptions and potentially bias the estimated coefficients through omitted-variable channels. Finally, high inter-item correlations, reaching $r = 0.80$, inflate standard errors and reduce the precision of estimates for more collinear predictors. In addition, Astana, where most central ministries are located, accounts for only 0.2% of the sample. The findings therefore generalise more confidently to regional and local governance structures than to the national capital.

4. 5. A FUTURE RESEARCH AGENDA

The limitations outlined above point to a clear agenda for future research. The most important next step is to move from a cross-sectional to a longitudinal research design. A panel study that re-surveys the same civil servants annually, ideally linked to administrative records in E-Kyzmet, would make it possible to assess whether the associations identified here reflect causal relationships. For example, such a design could determine whether participation in innovation projects improves perceptions of HRM quality or whether more motivated officials are simply more likely to participate in such projects. A quasi-experimental evaluation of a targeted AI-training programme, comparing equipped and authorised units with matched control groups, would provide even stronger evidence on which interventions effectively reduce the AI adoption gap. Second, explaining the remaining unexplained variance requires richer institutional-level measurement. Future survey waves should include organisational covariates such as regional budget per employee, leadership stability at the unit level, and objective indicators of digital infrastructure. This would allow future studies to move beyond individual perceptions towards multilevel mixed-effects models that distinguish individual-level from organisation-level influences and reduce omitted-variable bias. Methodologically, principal component regression or structural equation modelling could also complement the present analysis by addressing collinearity among closely related predictors. Third, the gender and tenure gaps in AI adoption should be examined through qualitative research. Semi-structured interviews and focus groups with female and long-serving civil servants would help identify mechanisms that survey data cannot fully capture, including time constraints, access to informal networks, managerial approval, and perceptions of AI relevance. A mixed-methods research programme combining longitudinal survey data, administrative records, and targeted qualitative fieldwork would therefore transform the descriptive evidence presented in this study into stronger causal and policy-relevant guidance for civil service reform.

5. CONCLUSION

What determines how civil servants in Kazakhstan assess HRM quality in their field? The findings suggest that the answer operates at several levels. At the individual level, education and patriotism emerge as the strongest predictors, consistent with the public service motivation literature and the human-centric emphasis on professional foundations. At the organisational level, the results reveal a more unexpected pattern: participation in innovative and strategic work is a stronger predictor of perceived HRM quality than leadership quality or access to digital tools, yet it is also the factor rated as least available. Career trajectory is another critical concern, receiving the lowest rating among all 14 items, showing the greatest variation in responses, and displaying the sharpest divide between managers and non-managerial staff. The AI findings reflect the same institutional logic but point to a distinct reform challenge. Roughly one-third of civil servants use AI tools with some regularity, while a substantial

additional share would like to use them but lack access or permission. The regression results show that the barriers to AI adoption are primarily positional and organisational rather than motivational or educational. Women and longer-serving officials report the lowest adoption rates and given their substantial presence in the civil service workforce, they cannot be treated as peripheral groups. The most desired AI applications writing assistance, translation, and data processing are routine administrative tools rather than advanced strategic systems. Providing reliable access to these tools, together with appropriate training and clear managerial authorisation, would address a concrete and widely shared constraint at relatively modest cost. Taken together, the findings support an ecosystem interpretation of Kazakhstan's civil-service HRM challenge in a practical rather than purely conceptual sense. Perceptions of HRM quality are shaped by the interaction of individual capacities, organisational conditions, and wider institutional arrangements; no single factor dominates. The results therefore point to the need for a coordinated, multi-level reform agenda focused on sustained professional development, stronger competency-building, expanded opportunities for meaningful project-based work, more transparent career pathways, and targeted AI-adoption programmes that prioritise the gender and tenure groups facing the largest aspiration, access gap. These contributions should be interpreted considering the study's limitations. The evidence is cross-sectional and self-reported, based on a single survey wave distributed through official channels. The analysis identifies robust associations but cannot establish causality, and approximately 60% of the variance in HRM quality perceptions remains unexplained by the individual-level factors measured here. Future research should therefore adopt longitudinal and quasi-experimental designs, incorporate organisation-level variables through multilevel modelling, and use qualitative methods to examine the mechanisms behind gender and tenure gaps in AI adoption. With these caveats, the survey provides a strong empirical starting point, and the Academy of Public Administration and ACSA are well positioned to advance the reform agenda implied by the findings.

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Author Contributions

Conceptualisation, A.Zh. and S.I.; methodology, S.S. and A.Zh.; software, A.Zh.; validation, S.S. and A.D.; formal analysis, A.Zh. and A.A.; investigation, A.Zh., S.I., A.A., A.D. and S.S.; resources, A.Zh. and S.I.; data curation, A.D. and S.S.; writing — original draft preparation, A.Zh.; writing — review and editing, S.I., A.A., A.Zh., A.D. and S.S.; visualisation, A.Zh. and A.A.; supervision, A.A. and S.I.; project administration, A.A.; funding acquisition, A.A. and S.I. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Survey microdata are available from the Academy of Public Administration upon reasonable request, subject to the data-governance regulations of the Republic of Kazakhstan.

Conflicts of Interest

The authors declare no conflict of interest.

6. TECHNICAL PRESENTATION

Table 1. Socio-demographic profile of respondents (N = 12,562)

Characteristic	Category	n (%)
Gender	Female	7,734 (61.6%)
	Male	4,828 (38.4%)
Age	Under 25	884 (7.0%)
	26–35	3,312 (26.4%)
	36–45	3,951 (31.5%)
	46–55	2,668 (21.2%)
	Over 55	1,747 (13.9%)
Education	College graduate	1,039 (8.3%)
	Bachelor / Specialist	9,744 (77.6%)
	Master's	915 (7.3%)
	PhD / Candidate of Sciences	25 (0.2%)
	Other	827 (6.6%)
Civil service tenure	Less than 3 years	2,337 (18.6%)
	3–5 years	939 (7.5%)
	5–10 years	2,212 (17.6%)
	10–15 years	2,011 (16.0%)
	15–20 years	1,837 (14.6%)
	More than 20 years	3,226 (25.7%)
Position level	Executive (non-managerial)	9,923 (79.0%)
	Managerial	2,639 (21.0%)
Level of government	Local executive body	7,780 (61.9%)
	Territorial ministry department	3,059 (24.4%)
	Central government body	692 (5.5%)
	Other	1,031 (8.2%)

Source: Authors' calculations

Table 2. Internal (individual-level) HRM quality factors: descriptive statistics by position level

Factor	M (SD) overall	Managers M	Executives M	Rank
Competency level	4.40 (0.87)	4.48	4.37	1
Patriotism / PSM	4.40 (0.93)	4.46	4.38	1
Education level	4.38 (0.88)	4.46	4.36	3
Continuous professional development	4.29 (0.99)	4.39	4.27	4
Specialised sectoral knowledge	4.28 (0.97)	4.38	4.25	5
Career trajectory	4.06 (1.11)	4.22	4.01	6

Source: Authors' calculations

Table 3. External (organisational/institutional) HRM quality factors: descriptive statistics by position level

Factor	M (SD) overall	Managers M	Executives M	Rank
Leadership and management style	4.28 (0.99)	4.41	4.24	1
Comfortable work environment	4.27 (1.00)	4.37	4.25	2
Transparency of performance eval.	4.22 (1.07)	4.34	4.19	3
Career-advancement transparency	4.14 (1.11)	4.30	4.10	4
Access to digital tools	4.12 (1.08)	4.21	4.10	5
Social guarantees / work conditions	4.11 (1.15)	4.23	4.08	6
Inter-departmental communication	4.10 (1.10)	4.19	4.08	7
Participation in innovation projects	3.99 (1.14)	4.07	3.97	8

Source: Authors' calculations

Table 4. OLS regression: determinants of perceived HRM quality (N = 10,826)

Variable	β	Robust SE	t	p
Constant	0.876	0.073	12.027	0.000***
Int: Education level	0.187	0.021	8.843	0.000***
Int: Competency level	0.108	0.024	4.452	0.000***
Int: Patriotism	0.122	0.018	6.825	0.000***
Int: Career trajectory	0.067	0.016	4.228	0.000***
Int: Specialised knowledge	0.014	0.019	0.729	0.466
Int: Continuous development	0.023	0.019	1.176	0.240
Ext: Work environment	0.066	0.019	3.556	0.000***
Ext: Leadership style	0.083	0.020	4.254	0.000***
Ext: Career transparency	-0.020	0.020	-1.028	0.304
Ext: Social guarantees	-0.009	0.016	-0.558	0.577
Ext: Innovation participation	0.097	0.017	5.739	0.000***
Ext: Digital tools	0.008	0.017	0.462	0.644
Ext: Inter-dept communication	0.000	0.018	0.025	0.980
Ext: Performance evaluation	0.070	0.018	3.859	0.000***
Female (=1)	-0.082	0.017	-4.872	0.000***
Age group	-0.007	0.010	-0.703	0.482
Education level (control)	-0.148	0.020	-7.302	0.000***
Civil-service tenure	0.020	0.007	3.091	0.002**
Manager (=1)	-0.063	0.020	-3.111	0.002**
Government level	0.010	0.013	0.735	0.463

Notes: Dependent variable: overall civil-service HRM quality (1–5). HC1 robust standard errors. $R^2 = 0.398$; Adj. $R^2 = 0.397$; $F(20, 10,805) = 357.3$, $p < 0.001$. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Source: Authors' calculations

Table 5. Binary logit: determinants of current AI-tool usage (N = 11,735)

Variable	β	OR	SE	z	p
Constant	-0.153	0.858	0.164	-0.931	0.352
Int: Competency level	-0.088	0.915	0.036	-2.477	0.013*
Int: Continuous development	-0.055	0.946	0.036	-1.544	0.123
Int: Career trajectory	0.036	1.037	0.030	1.199	0.231
Ext: Digital tools access	0.080	1.084	0.033	2.442	0.015*
Ext: Innovation participation	0.042	1.043	0.032	1.305	0.192
Female (=1)	-0.232	0.793	0.044	-5.311	0.000***
Age group	-0.083	0.921	0.027	-3.089	0.002**
Education level	0.051	1.053	0.050	1.021	0.307
Civil-service tenure	-0.170	0.844	0.017	-10.026	0.000***
Manager (=1)	0.499	1.647	0.054	9.277	0.000***

Notes: Dependent variable: current AI use (daily or weekly = 1). McFadden $R^2 = 0.032$; accuracy = 71.3%. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Source: Authors' calculations

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