IRSTI 15.21.45 https://doi.org/10.26577/JPsS20269831

M. Abdykalikova[1], T. Kaldybayev[2],
A. Bolatov[1,3], N. Bozymbayeva[4*]

[1]Eurasian National University, Astana, Kazakhstan
[2]Almaty Management University, Almaty, Kazakhstan
[3]Shenzhen University, Shenzhen, China
[4]Maqsut Narikbayev University, Astana, Kazakhstan
*e-mail: nbozymbaeva@gmail.com

PSYCHOLOGICAL FACTORS INFLUENCING THE ACCEPTANCE OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES AMONG CIVIL SERVANTS IN KAZAKHSTAN

Artificial intelligence (AI) technologies are increasingly being introduced into the public sector; however, the effectiveness of their implementation largely depends on civil servants' readiness to use digital solutions. Despite growing interest in this field, empirical evidence on the psychological factors underlying AI acceptance in public administration in Central Asian countries remains limited. The aim of this study was to identify psychological predictors of Kazakhstani civil servants' behavioral intention to use artificial intelligence technologies. A cross-sectional study was conducted among 170 civil servants. Structural equation modeling using the WLSMV estimator was applied to analyze the data. The study examined perceived usefulness and ease of use of AI, attitudes toward the technology, trust in AI and automation, perceived behavioral control, and self-efficacy. The results showed that perceived usefulness of AI was the strongest positive predictor of behavioral intention ($\beta = 0.603$; $p < 0.001$). Significant positive associations were also found for trust in AI, perceived behavioral control, and positive attitudes toward the technology, whereas trust in automation was negatively associated with behavioral intention. The association between age and self-efficacy differed depending on the language in which the questionnaire was completed. The scientific value of the study lies in advancing the understanding of the psychological mechanisms underlying AI acceptance in Kazakhstan's public sector and contributing empirical evidence from the Central Asian context. The practical significance of the findings lies in their potential application to the development of training and organizational support programs for civil servants in the context of digital transformation.

Keywords: artificial intelligence, psychological predictors, civil servants, technology acceptance, behavioral intention, trust in AI, structural equation modeling.

М.Н. Абдықалықова[1], Т.Н. Калдыбаев[2],
А. Болатов[1,3], Н.А. Бозымбаева[4*]

[1]Л.Н. Гумилев атындағы Еуразия ұлттық университеті, Астана, Қазақстан
[2]Almaty Management University, Алматы, Қазақстан
[3]Шэньчжэнь университеті, Шэньчжэнь, Қытай
[4]Maqsut Narikbayev University, Астана, Қазақстан
*e-mail: nbozymbaeva@gmail.com

Қазақстандағы мемлекеттік қызметшілердің жасанды интеллект технологияларына көзқарасының психологиялық факторлары

Жасанды интеллект (ЖИ) технологиялары мемлекеттік секторға барған сайын кеңінен енгізілуде, алайда оларды қолданудың тиімділігі көбіне мемлекеттік қызметшілердің цифрлық шешімдерді пайдалануға дайындығына байланысты. Бұл мәселеге қызығушылықтың артуына қарамастан, Орталық Азия елдерінің мемлекеттік басқару жүйесінде ЖИ-ді қабылдауға ықпал ететін психологиялық факторлар туралы эмпирикалық деректер әлі де шектеулі. Зерттеудің мақсаты – Қазақстандағы мемлекеттік қызметшілердің жасанды интеллект технологияларын пайдалануға деген мінез-құлықтық ниетінің психологиялық предикторларын анықтау. Көлденең зерттеуге 170 мемлекеттік қызметші қатысты. Деректерді талдау үшін WLSMV бағалаушысын қолдану арқылы құрылымдық теңдеулерді модельдеу әдісі пайдаланылды. Зерттеуде ЖИ-дің қабылданатын пайдалылығы мен қолдану жеңілдігі, технологияға деген көзқарас, ЖИ мен автоматтандыруға деген сенім, қабылданатын мінез-құлықтық бақылау және өзіндік тиімділік қарастырылды. Нәтижелер ЖИ-дің қабылданатын пайдалылығы мінез-құлықтық ниеттің ең күшті оң предикторы болғанын

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көрсетті (β = 0,603; p < 0,001). ЖИ-ге деген сенім, қабылданатын мінез-құлықтық бақылау және технологияға деген оң көзқарас бойынша да статистикалық мәнді оң байланыстар анықталды, ал автоматтандыруға деген сенім мінез-құлықтық ниетпен теріс байланысты болды. Жас пен өзіндік тиімділік арасындағы байланыс сауалнаманы толтыру тіліне байланысты ерекшеленді. Зерттеудің ғылыми құндылығы Қазақстанның мемлекеттік секторында ЖИ-ді қабылдаудың психологиялық механизмдері туралы түсініктерді кеңейтумен және Орталық Азия контексіндегі эмпирикалық деректерді толықтырумен айқындалады. Нәтижелердің практикалық маңыздылығы оларды цифрлық трансформация жағдайында мемлекеттік қызметшілерді оқыту және ұйымдастырушылық қолдау бағдарламаларын әзірлеуде пайдалану мүмкіндігімен анықталады.

Түйін сөздер: жасанды интеллект, психологиялық предикторлар, мемлекеттік қызметшілер, технологияны қабылдау, мінез-құлықтық ниет, ЖИ деген сенім, құрылымдық теңдеулерді модельдеу.

М.Н. Абдыкаликова[1], Т.Н. Калдыбаев[2],
А. Болатов[1, 3], Н.А. Бозымбаева[4*]

[1]Евразийский национальный университет имени Л.Н. Гумилева, Астана, Казахстан
[2]Almaty Management University, Алматы, Казахстан
[3]Шэньчжэньский университет, Шэньчжэнь, Китай
[4]Maqsut Narikbayev University, Астана, Казахстан
*e-mail: nbozymbaeva@gmail.com

Психологические факторы представления технологий искусственного интеллекта государственными служащими в Казахстане

Технологии искусственного интеллекта (ИИ) все активнее внедряются в государственный сектор, однако эффективность их применения во многом определяется готовностью государственных служащих к использованию цифровых решений. Несмотря на растущий интерес к данной проблематике, эмпирические данные о психологических факторах принятия ИИ в государственном управлении стран Центральной Азии остаются ограниченными. Цель исследования – выявить психологические предикторы поведенческого намерения государственных служащих Казахстана использовать технологии искусственного интеллекта. В поперечном исследовании приняли участие 170 государственных служащих. Для анализа данных применялось моделирование структурными уравнениями с использованием оценщика WLSMV. Исследовались воспринимаемая полезность и простота использования ИИ, отношение к технологии, доверие к ИИ и автоматизации, воспринимаемый поведенческий контроль и самоэффективность. Результаты показали, что наиболее сильным положительным предиктором поведенческого намерения являлась воспринимаемая полезность ИИ (β = 0,603; p < 0,001). Значимые положительные связи также выявлены для доверия к ИИ, воспринимаемого поведенческого контроля и позитивного отношения к технологии, тогда как доверие к автоматизации было отрицательно связано с поведенческим намерением. Связь возраста с самоэффективностью различалась в зависимости от языка заполнения опросника. Научная ценность исследования заключается в расширении представлений о психологических механизмах принятия ИИ в государственном секторе Казахстана и дополнении эмпирических данных по Центральной Азии. Практическая значимость результатов определяется возможностью их использования при разработке программ обучения и организационной поддержки государственных служащих в условиях цифровой трансформации.

Ключевые слова: искусственный интеллект, психологические предикторы, государственные служащие, принятие технологий, поведенческое намерение, доверие к ИИ, моделирование структурных уравнений.

Introduction

The integration of artificial intelligence (AI) systems in public administration stands as one of the most impactful changes in modern governance. The Public Sector AI Adoption Index (2026) reveals that 74% of civil servants across ten countries use AI in their work, yet just 18% feel their governments are effectively overseeing this integration. This disparity prompts an important question: what psychological and contextual factors influence or hinder civil servants' willingness to engage with AI tools?

Kazakhstan is a particularly relevant context for this study. The country ranks 24th in the UN e-Government Development Index (EGDI): over 90% of public services have been transferred online, and investment in AI has increased fivefold to $73 million (Kazakhstan First Country AI Report, 2025; eGov.kz, 2025). At the same time, official bilingualism (Kazakh and Russian), post-Soviet bureaucratic culture, and regional digital divide form a unique combination of factors not represented in the international literature (Alibekova et al., 2020).

Despite the growing body of research on AI acceptance, several important gaps remain. First, most empirical studies have been conducted in corporate, educational, or healthcare settings, whereas the psychological determinants of AI acceptance among civil servants have received considerably less attention. Second, the available evidence is largely based on data from high-income Western or East Asian countries, limiting the generalizability of existing models to post-Soviet and Central Asian contexts. Third, previous studies have primarily emphasized technological and organizational determinants of AI adoption, while the combined role of psychological factors – including trust in AI, trust in automation, perceived behavioral control, self-efficacy, and language-related differences – has rarely been examined within a unified structural model. Addressing these gaps is important for understanding AI acceptance in public administration and for extending existing psychological models of technology acceptance to underrepresented institutional and cultural settings.

This study addresses these gaps by identifying the factors that drive Kazakh civil servants' behavioral intention to use AI technologies. Employing ordinal structural equation modeling (WLSMV estimator in Mplus), we tested an integrated model incorporating perceived usefulness (PU), perceived ease of use (PEU), attitude toward AI (ATT), trust in AI (TRUST), trust in automation (S-TIAS), perceived behavioral control (PBC), and self-efficacy (SE). Additionally, we explored whether the relationship between age and self-efficacy differs across language groups. By integrating constructs from the Technology Acceptance Model (TAM; Davis, 1989), the Theory of Planned Behavior (TPB; Ajzen, 1991), and automation trust theory (Lee & See, 2004), this study contributes to psychological research on AI acceptance by extending these frameworks to the context of public administration in Kazakhstan and providing empirical evidence from an underrepresented Central Asian setting.

Literature review

Civil servants face mandatory accountability, and errors in algorithms carry both legal and reputational risks – setting them apart fundamentally from users in the private sector (Alon-Barkat & Busuioc, 2022). According to Ahn and Chen (2022), US officials generally have a positive view of AI (average rating of 5.4 out of 7), though they worry about losing professional autonomy. Haesevoets et al. (2025) found that employees tend to prefer AI as a tool that supports decision-making rather than as an independent decision-maker; managers show greater AI readiness than frontline staff. In a study of 690 US municipal officials, Horowitz and Kahn (2021) identified that direct experience with AI applications most strongly correlates with positive attitudes toward the technology. Neumann et al. (2024), analyzing data from the Philippines, confirmed that management backing is vital during the design phase, but weak infrastructure consistently obstructs implementation. Amanbek et al. (2020) applied the Technology Acceptance Model (TAM) in Kazakhstan ($n = 300$) and observed that while the eGov portal was seen as highly useful, regular use was low due to trust issues and technical difficulties.

This study is grounded in the Technology Acceptance Model (TAM; Davis, 1989) combined with the Theory of Planned Behavior (TPB; Ajzen, 1991). TAM suggests that the intention to use technology depends on perceived usefulness (PU) – a subjective judgment of how much it enhances professional effectiveness – and perceived ease of use (PEU), which influences both PU and behavioral intention. The TAM2 extension (Venkatesh & Davis, 2000) accounts for 34–52% of the variance in intention, while the unified theory UTAUT (Venkatesh et al., 2003) explains up to 70%. TPB adds perceived behavioral control (PBC) and subjective norms, which, together with attitude (ATT), shape behavioral intention.

TAM (Davis, 1989) suggests that behavioral intention is influenced by perceived usefulness (PU) and perceived ease of use (PEU). Later, Venkatesh and Davis (2000) extended this to TAM2, which accounts for 34–52% of the variance in intention. The UTAUT model (Venkatesh et al., 2003) combined eight different models, explaining up to 70% of intention variance. TPB (Ajzen, 1991) introduces perceived behavioral control (PBC), reflecting how easy or difficult someone believes performing an action is, given their available resources. Rathnayake et al. (2025) confirmed the sequence TRUST→PEU→PU→ATT→BI within the Sri Lankan public sector ($n = 380$). Using a sample from education, Du and Li (2026) found self-efficacy (SE) to be the strongest predictor of intention, even more than social influence.

The proposed conceptual model integrates complementary psychological constructs derived from the Technology Acceptance Model (TAM), the

Theory of Planned Behavior (TPB), and automation trust theory to explain AI acceptance among civil servants. Within this framework, perceived ease of use and perceived usefulness represent the cognitive evaluation of AI technologies, while attitude reflects the individual's overall affective evaluation of their use. Perceived behavioral control and self-efficacy capture beliefs about one's capability and available resources to use AI effectively. Trust in AI and trust in automation represent relational mechanisms that reduce uncertainty associated with algorithmic decision-making, which is particularly relevant in the public sector where accountability and perceived risks are high. By integrating these cognitive, affective, and control-related mechanisms into a single structural model, the study provides a comprehensive explanation of the psychological processes underlying behavioral intention to use AI technologies.

By merging these theories, we obtain a thorough framework to examine the cognitive, emotional, and situational factors behind AI adoption in public organizations. Building on this framework, the following hypotheses are proposed:

H1. Perceived usefulness is positively associated with behavioral intention to use AI technologies.
H2. Perceived ease of use is positively associated with perceived usefulness.

H3. Perceived usefulness is positively associated with attitude toward AI technologies.

H4. Attitude is positively associated with behavioral intention.

Trust plays a key role in predicting AI adoption. A meta-analysis by Kaplan et al. (2023) showed that perceived reliability, system competence, and anthropomorphic traits reliably influence trust in AI. In the public sector, trust in government agencies transfers to their AI systems through an institutional mechanism (Kasilingam, 2020). Yet, trust in algorithms is delicate: a single error observed in a system leads to a sharper and longer-lasting drop in trust compared to a similar mistake by a human expert (Dietvorst et al., 2015). Meanwhile, Lee and See (2004) defined trust in automation as the willingness to depend on an automated system amid uncertainty, which involves three components: perceived performance, correctness of the process, and how well system goals align with those of the user. The link between this trust and behavioral intention is complex: while high trust can boost intention, it can also cause uncritical reliance, potentially weakening an official's professional duty. Based on this:

H5. Trust in AI is positively associated with behavioral intention.

H6. Trust in automation is associated with behavioral intention, but the direction of this association is examined empirically.

Perceived behavioral control (PBC) related to public technologies involves two key parts: a resource component, which includes access to regulations, training, technical support, and licensed software, and a competency component, referring to an individual's confidence in their ability to use the system effectively. Research consistently shows that without enabling factors like stable internet access, corporate licenses, and dedicated training time, even the most motivated employees struggle to turn their intentions into actual usage (Venkatesh et al., 2003). In Kazakhstan, digital inequality across regions leads to structural differences in PBC. For instance, AI platforms such as Smart Data Ukimet are mostly available in Astana and Almaty, whereas district administrations often face outdated infrastructure and a lack of IT staff (Kogabayev & Banerjee, 2024).

Although conceptually distinct, self-efficacy is closely related to perceived behavioral control because both constructs reflect individuals' beliefs about their capability to perform a behavior. However, whereas perceived behavioral control encompasses both internal capabilities and external facilitating conditions, self-efficacy specifically refers to an individual's confidence in their ability to successfully perform technology-related tasks (Compeau & Higgins, 1995). In the present study, self-efficacy complements perceived behavioral control by capturing confidence in using AI technologies beyond perceptions of organizational resources and support.

Recent research highlights two major roles of self-efficacy. First, it exerts a direct effect on technology acceptance: Joo et al. (2018) found that self-efficacy reduced technostress and enhanced perceived ease of use among Korean teachers. Second, it operates through indirect mechanisms. Li et al. (2024) identified a fully mediated pathway in which self-efficacy increased motivation, leading to greater cognitive engagement and, ultimately, stronger behavioral intention ($\beta = 0.43$, $p < .001$). Furthermore, self-efficacy functions as a psychological resource that reduces fear of unfamiliar technologies and facilitates adaptation to technological change. This role is particularly important in public organizations, where concerns about job displacement, accountability, and reduced professional autonomy may hinder AI adoption (Barodi & Lalaoui, 2025). Based on this reasoning, the following hypothesis is proposed:

H7. Perceived behavioral control is positively associated with behavioral intention.

The connection between age and technological self-efficacy varies across studies. In a systematic review, Caputo et al. (2025) reported that while some research found no significant direct link between age and intention, others observed moderate negative correlations; notably, structured training tended to reduce these age-related differences. Using a sample of 375 elderly smart app users in China, Liu and Md Kassim (2026) demonstrated that attitudes, trust, and life satisfaction were strong predictors of intention even among older adults, suggesting a nonlinear effect of age.

The theoretical framework rests on two main concepts. First, cognitive load theory (Sweller, 2011) suggests that processing technical information in a language other than one's primary one significantly raises extraneous cognitive load, which in turn drains working memory and lowers perceived ease of use (PEU). Second, Green and Abutalebi's (2013) adaptive control hypothesis argues that frequent switching between two languages in young bilinguals strengthens executive functions, boosting cognitive flexibility and improving adaptability to new technology—an effect that helps explain age differences within that group. Empirical evidence for language's moderating role in the Technology Acceptance Model (TAM) comes from Hou et al. (2026), who found that language proficiency notably moderates the pathway from PEU to perceived usefulness (PU) in adopting AI platforms. This finding supports the eighth hypothesis:

H8. Age is associated with self-efficacy, and this association differs by language group.

Kazakhstan stands out as the clear leader in digital public administration across Central Asia. Globally, it ranks 24th in the UN e-Government Development Index (EGDI), reflecting the high level of technological advancement in its public infrastructure (Kazakhstan Digital Government Moment, 2025). The eGov Mobile portal boasts 11 million active users, while digital documents were accessed 41 million times during the first half of 2025 (eGov.kz, 2025). Investments in AI have surged fivefold to $73 million, and the government is working on a National AI Platform that emphasizes creating Kazakh-language models (Kazakhstan First Country AI Report, 2025).

Yet, this technological edge brings a notable contradiction: despite the ambitious infrastructure, there's a gap in understanding the psychological factors affecting its adoption by the very civil servants responsible for its implementation. Most existing research targets citizens as public service users (Amanbek et al., 2020; Bokayev et al., 2021; ENU E-Government Portal Study, 2022), leaving little insight into how officials view the shift from basic digital services to AI-driven intelligent automation.

On a broader scale, Alibekova et al. (2020) conducted a comparative study with Turkey and Korea and highlighted systemic obstacles in Kazakhstan's digital transformation – namely, a shortage of IT specialists, digital disparities across regions, and a conservative organizational culture within government bodies. Earlier, Bhuiyan (2011) examined Kazakhstan's initial e-government phase and revealed that bureaucratic resistance is deeply embedded, meaning it can't be resolved solely through administrative actions without addressing underlying psychological dynamics.

A closely related example comes from Uzbekistan, where Avazov and Lee (2022) tested an extended version of the Unified Model of E-Government Acceptance (UMEGA) with a sample of 390 citizens. They found that the strongest predictors for the intention to use e-government services were expected performance ($\beta = 0.680$) and trust ($\beta = 0.548$). Notably, both the direction and strength of these relationships in Uzbekistan differed from Western norms, which the authors link to cultural values like collectivism and high power distance – traits also characteristic of Kazakhstani society.

Supporting this, data from a comparative study by Hofstede (Jan et al., 2024) show that cultural dimensions significantly influence the strength of connections within TAM/UTAUT models. For instance, in high-power-distance societies such as Kazakhstan, social influence and institutional pressure play a far stronger role in shaping behavioral intentions than they do in individualistic Western countries. This suggests that applying Western AI adoption models directly to Kazakhstan without accounting for cultural differences is methodologically flawed.

An examination of the international literature highlights three overlapping research gaps that together form the foundation for this study's scientific contribution.

The first gap is organizational. Although there's plenty of research on AI adoption in fields like education, healthcare, and the private sector, empirical studies that explore what drives civil servants – who use AI professionally in decision-making roles – to intend to use AI are still seriously lacking (Haesevoets et al., 2025). Most existing research in the public sector concentrates either on citizens as recipients of services (Amanbek et al., 2020; Avazov & Lee, 2022) or examines AI adoption at the organizational decision-making level (Neumann et al., 2024).

The second gap is geographical. The bulk of international literature comes from countries such as the United States, United Kingdom, the Netherlands, Singapore, and the Gulf States. Despite the fast-paced digital transformation of public administration in Kazakhstan and Uzbekistan, Central Asia hardly appears at all in Scopus and Web of Science databases when it comes to the psychological factors influencing AI adoption among civil servants. To our knowledge, this study is the first quantitative psychological investigation using structural modeling to analyze the behavioral intention to use AI among civil servants in Kazakhstan.

The third gap concerns sociolinguistics. None of the existing TAM/UTAUT studies in the region have explored how institutional bilingualism moderates the link between age, self-efficacy, and AI adoption. Kazakhstan offers a unique natural experiment to investigate this, given its official Kazakh-Russian bilingualism, active policy promoting language transition in government affairs, and simultaneous localization of AI systems into Kazakh. Understanding how self-efficacy varies across language groups here could provide an original contribution to the broader technology acceptance theory by highlighting sociolinguistic factors as key moderators of cognitive predictors.

Materials and methods

The study was conducted using a quantitative cross-sectional survey design. This design is used when it is necessary to simultaneously examine multiple psychological constructs in a heterogeneous professional sample and is standard for technology adoption studies using structural modeling. The cross-sectional nature of data collection means that measurements were taken only once, which precludes establishing causal relationships but does allow for testing theoretically grounded associations between latent constructs within a single analytical model.

Participants included civil servants from central and regional executive bodies. The choice of this context was motivated by three considerations: (1) the Kazakhstani public sector represents a unique combination of rapid digitalization and the institutional characteristics of post-Soviet bureaucracy; (2) official bilingualism (Kazakh and Russian) creates the opportunity to test sociolinguistic moderation of psychological predictors of technology adoption; (3) empirical psychological studies of AI adoption in the Central Asian public sector are virtually absent from Scopus and Web of Science databases. Data were collected using a structured self-report questionnaire distributed to civil servants. The questionnaire was available in two language versions – Kazakh and Russian – to allow respondents to respond in their preferred professional language and to generate the language group variable used in the moderator analyses.

The study involved 170 civil servants. All participants were employed by the civil service at the time of data collection and directly used digital tools in their professional activities. Inclusion criteria included: official civil servant status in accordance with the Law of the Republic of Kazakhstan «On Civil Service»; regular use of a computer or mobile device for work purposes; and voluntary informed consent to participate. Exclusion criteria included: being on vacation or sick leave during the data collection period; and refusal to sign informed consent.

The sample was formed using convenience sampling with elements of purposive selection: invitations to participate were sent to government agencies, taking into account coverage of different levels of government (central and regional). This approach is common in organizational psychological research, where access to a professional sample is limited by departmental procedures. It should be noted that convenience sampling limits the generalizability of the results to the general population of Kazakhstani civil servants, which numbers over 90,000 people. Of the total number of participants ($n = 170$), all observations were retained in the final analysis: inspection of patterns of missing values – coded as – 99 – indicated completeness of data for all variables in the final SEM model.

All constructs were measured using adapted versions of validated psychometric scales using the Likert scale. The scales were back-translated into Kazakh and Russian to ensure semantic equivalence. The items were adapted to the professional context of public service.

During confirmatory factor analysis, several items were excluded from the final model due to local inconsistency or cross-construct overlap.

Statistical analyses were conducted using Jamovi version 2.6.17 and Mplus version 8.5. The analysis followed a latent-variable structural equation modeling approach to evaluate both the measurement properties of the questionnaire constructs and the theoretically specified relationships among them. The final analytic sample included 170 civil servants.

First, descriptive analyses were conducted to characterize the study sample and inspect the distribution of observed variables. Age was treated as a continuous variable, while sex and language group were treated as categorical variables. For all questionnaire items, response frequencies and proportions were examined to assess the distribution of ordinal responses and to identify sparse response categories. Because the substantive questionnaire items were measured using Likert-type ordinal scales, they were specified as ordered categorical indicators in the SEM analysis.

Missing values were coded as -99. In the final Mplus model, one missing-data pattern was identified, indicating complete data for the variables included in the final SEM model. Therefore, all 170 observations were retained in the final analysis.

The SEM model was estimated using the weighted least squares mean- and variance-adjusted estimator. The THETA parameterization was used, and a probit link function was applied for the ordinal indicators. This estimation strategy was selected because it is appropriate for models with ordered categorical indicators and latent variables.

The analysis proceeded in two main stages. First, the measurement component of the model was evaluated using confirmatory factor analysis within the SEM framework. Eight latent constructs were specified: STIAS, perceived ease of use, perceived usefulness, perceived behavioral control, behavioral intention, attitude, trust, and self-efficacy. The retained indicators were STIAS1–STIAS3 for STIAS; PEU1, PEU2, and PEU4 for perceived ease of use; PU1-PU4 for perceived usefulness; PBC1, PBC2, and PBC4 for perceived behavioral control; BI1-BI4 for behavioral intention; A1, A2, A4, A5, and A6 for attitude; T1, T3, T4, T6, T7, and T8 for trust; and SE1-SE6 for self-efficacy. Standardized factor loadings were inspected to evaluate the strength of the associations between each observed indicator and its corresponding latent construct.

Second, the structural component of the model was estimated to test the hypothesized relationships among the latent constructs. Behavioral intention was specified as the primary endogenous outcome and was regressed on attitude, perceived usefulness, trust, STIAS, and perceived behavioral control. Attitude was regressed on perceived usefulness. Perceived usefulness was regressed on perceived ease of use and trust. Perceived ease of use was regressed on STIAS. These paths were specified to examine how technology-related beliefs, trust, perceived control, and attitudes were associated with civil servants' intention to use AI technologies in public-sector work. Covariances were specified among theoretically relevant upstream constructs. STIAS was allowed to covary with perceived behavioral control and self-efficacy. Perceived behavioral control was allowed to covary with self-efficacy. Trust was allowed to covary with self-efficacy, STIAS, and perceived behavioral control. These covariances were included to account for conceptual overlap among background perceptions, trust-related beliefs, perceived capacity, and confidence in using AI-related technologies.

A limited number of residual covariances were added between closely related indicators within the same latent construct when theoretically plausible and empirically justified. Specifically, residual covariances were specified between STIAS2 and STIAS3, T4 and T8, A4 and A5, and PBC2 and PBC4. These correlated residuals were retained because the item pairs were conceptually similar and belonged to the same construct, suggesting shared item-specific variance beyond the general latent factor.

In addition to the main structural model, moderation analysis was conducted to examine whether the association between age and self-efficacy differed by language group. Age was mean-centered using the sample mean of 37.8 years. An interaction term was created by multiplying centered age by language group. Self-efficacy was then regressed on centered age, language group, and the Age × Language interaction term. The coefficient for centered age represented the simple slope of age for the reference language group, while the interaction term represented the difference in the age slope between language groups. Simple slopes were estimated using the MODEL CONSTRAINT command: the age slope for the reference language group was defined as the centered-age coefficient, and the age slope for the comparison language group was calculated as the sum of the centered-age coefficient and the interaction coefficient.

Model fit was evaluated using multiple indices: the chi-square test of model fit, root mean square error of approximation with 90% confidence interval, comparative fit index, Tucker–Lewis index, and standardized root mean square residual. Because the WLSMV chi-square statistic is sensitive to sample size and model complexity, model evaluation was based primarily on the combined interpretation of RMSEA, CFI, TLI, and SRMR rather than on the chi-square test alone.

Parameter estimates were reported as unstandardized and standardized coefficients. Standardized estimates were interpreted using the STDYX standardization, which is appropriate for models including categorical indicators and latent variables. Statistical significance was evaluated using two-tailed p values, with $p < .05$ considered statistically significant. Confidence intervals were requested for model parameters. Modification indices were not used in the final model output because Mplus does not provide modification indices when nonlinear constraints are specified through the MODEL CONSTRAINT command.

The study was conducted in accordance with ethical standards for research involving human participants. Ethical approval was obtained from the Ethics Committee of the Department of Psychology, Faculty of Journalism and Social Sciences, L.N. Gumilyov Eurasian National University (Protocol No. 2, September 30, 2025). Participation in the survey was voluntary. Prior to data collection, all participants received information about the purpose of the study, procedures, potential risks and benefits, and their right to withdraw from participation at any time without consequences. Informed consent was obtained from all participants before completing the questionnaire. The survey was anonymous, and no personally identifiable information was collected. All data were stored securely and used exclusively for scientific purposes.

Results and discussion

The final analytic sample included 170 participants. Of these, 74 were male (43.5%) and 96 were female (56.6%). Participants' mean age was 37.8 years (SD = 10.9), ranging from 21 to 63 years. Regarding survey language, 89 participants completed the Kazakh version (52.4%) and 81 completed the Russian version (47.6%). Before testing the structural model, we first examined the psychometric performance of the study scales, including item-level reliability, internal consistency, and descriptive properties.

Initial item-level reliability analysis was conducted for all study scales. Several reverse-coded items demonstrated low item-rest correlations and were therefore removed from subsequent analyses. Specifically, PEU3(R) was excluded due to a low item-rest correlation (IRC = 0.166), SN4(R) was removed because of low IRC (0.221), and PBC3(R) was excluded because of a relatively weak IRC (0.372) and improved reliability after deletion. Similarly, A3(R) and A7(R) were removed from the Attitudes scale due to low IRC values of 0.240 and 0.267, respectively.

After item removal, the retained items showed generally acceptable to excellent internal consistency (Table 1). The S-TIAS scale demonstrated excellent reliability, with Cronbach's $\alpha = 0.937$ and McDonald's $\omega = 0.939$. Perceived ease of use showed good reliability ($\alpha = 0.830$, $\omega = 0.845$), while perceived usefulness demonstrated excellent reliability ($\alpha = 0.950$, $\omega = 0.951$). Subjective norms showed acceptable reliability ($\alpha = 0.786$, $\omega = 0.814$), and perceived behavioral control showed good reliability ($\alpha = 0.863$, $\omega = 0.872$). Behavioral intention also demonstrated good internal consistency ($\alpha = 0.873$, $\omega = 0.888$). The Attitudes scale showed good reliability ($\alpha = 0.874$, $\omega = 0.878$), Trust showed excellent reliability ($\alpha = 0.923$, $\omega = 0.925$), and SE demonstrated excellent reliability ($\alpha = 0.943$, $\omega = 0.945$).

Table 1
Item-level descriptive statistics and internal consistency indices for retained scale items

Scale	Item	Mean (SD)	IRC	If item dropped	
				Cronbach's α	McDonald's ω
S-TIAS	S-TIAS1	4.52 (1.48)	0.817	0.950	0.950
	S-TIAS2	4.27 (1.45)	0.907	0.879	0.879
	S-TIAS3	4.31 (1.45)	0.887	0.895	0.895
PEU	PEU1	5.15 (1.44)	0.742	0.713	0.713
	PEU2	5.14 (1.49)	0.775	0.676	0.677
	PEU4	4.69 (1.52)	0.562	0.888	0.889
PU	PU1	5.19 (1.44)	0.844	0.945	0.945
	PU2	5.21 (1.48)	0.905	0.927	0.928
	PU3	5.14 (1.45)	0.912	0.925	0.926
	PU4	5.12 (1.45)	0.857	0.941	0.942

Table continued

Scale	Item	Mean (SD)	IRC	If item dropped	
				Cronbach's α	**McDonald's ω**
SN	SN1	3.24 (1.85)	0.693	0.634	0.641
	SN2	3.34 (1.86)	0.783	0.522	0.527
	SN3	4.65 (1.56)	0.438	0.885	0.885
PBC	PBC1	4.91 (1.64)	0.640	0.900	0.900
	PBC2	4.91 (1.56)	0.799	0.755	0.755
	PBC4	4.81 (1.63)	0.790	0.760	0.761
BI	BI1	5.44 (1.45)	0.805	0.807	0.835
	BI2	4.06 (1.04)	0.717	0.859	0.868
	BI3	5.06 (1.62)	0.814	0.802	0.832
	BI4	4.64 (1.71)	0.658	0.876	0.890
Attitudes	A1	5.41 (1.56)	0.708	0.848	0.855
	A2	5.18 (1.79)	0.641	0.863	0.869
	A4	5.25 (1.74)	0.701	0.848	0.853
	A5	5.31 (1.71)	0.790	0.827	0.832
	A6	5.03 (1.93)	0.690	0.853	0.854
Trust	T1	4.01 (1.70)	0.757	0.912	0.914
	T2	4.94 (1.47)	0.554	0.926	0.928
	T3	4.46 (1.54)	0.779	0.910	0.913
	T4	3.40 (1.69)	0.769	0.911	0.914
	T5	2.77 (1.67)	0.706	0.916	0.919
	T6	3.73 (1.66)	0.862	0.903	0.905
	T7	3.92 (1.63)	0.817	0.907	0.909
	T8	3.37 (1.81)	0.689	0.918	0.919
SE	SE1	2.50 (1.05)	0.725	0.945	0.946
	SE2	2.67 (1.00)	0.830	0.932	0.935
	SE3	2.69 (1.00)	0.887	0.925	0.927
	SE4	2.70 (0.95)	0.874	0.928	0.929
	SE5	2.57 (1.04)	0.836	0.932	0.934
	SE6	2.51 (1.04)	0.826	0.933	0.935

Note: Values are presented as mean and standard deviation unless otherwise indicated. IRC = item–rest correlation; S-TIAS = short-Trust in Automation Scale; PEU = perceived ease of use; PU = perceived usefulness; SN = subjective norms; PBC = perceived behavioral control; BI = behavioral intention; SE = self-efficacy. "If item dropped" refers to Cronbach's α and McDonald's ω recalculated after removing the corresponding item from the scale. Reverse-coded items with low item-rest correlations were excluded from the final scale scores: PEU3(R), SN4(R), PBC3(R), A3(R), and A7(R).

After confirming acceptable reliability of the retained items, scale-level descriptive statistics and bivariate correlations were examined to characterize the main study constructs and their preliminary associations.

Scale-level descriptive statistics indicated generally high endorsement of technology-related acceptance constructs (Table 2). The highest mean scores were observed for Attitudes (M = 5.24, SD = 1.43), perceived usefulness (M = 5.17, SD = 1.36), perceived ease of use (M = 5.00, SD = 1.28), perceived behavioral control (M = 4.88, SD = 1.43), and behavioral intention (M = 4.80, SD = 1.26). The mean score for S-TIAS was also relatively high (M = 4.36, SD = 1.37). Lower mean scores were observed for subjective norms (M = 3.74, SD = 1.47), trust (M = 3.82, SD = 1.33), and SE (M = 2.61, SD = 0.89).

Table 2
Scale-level descriptive statistics, reliability coefficients, and interscale correlations

Scale	Mean	SD	Cronbach's α	McDonald's ω	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
S-TIAS (1)	4.36	1.37	0.937	0.939	-							
PEU (2)	5.00	1.28	0.830	0.845	0.614	-						
PU (3)	5.17	1.36	0.950	0.951	0.449	0.760	-					
SN (4)	3.74	1.47	0.786	0.814	0.386	0.320	0.400	-				
PBC (5)	4.88	1.43	0.863	0.872	0.391	0.517	0.459	0.379	-			
BI (6)	4.80	1.26	0.873	0.888	0.482	0.655	0.731	0.399	0.510	-		
Attitudes (7)	5.24	1.43	0.874	0.878	0.279	0.439	0.478	0.250	0.350	0.522	-	
Trust (8)	3.82	1.33	0.923	0.925	0.550	0.535	0.528	0.515	0.404	0.637	0.326	-
SE (9)	2.61	0.89	0.943	0.945	0.333	0.362	0.354	0.338	0.337	0.443	0.266	0.640

Note: N = 170. Values on the diagonal are omitted. Correlation coefficients are Pearson's r. All scales were scored so that higher values indicate higher levels of the corresponding construct. Cronbach's α and McDonald's ω are reported as internal consistency estimates. S-TIAS = short-Trust in Automation Scale; PEU = perceived ease of use; PU = perceived usefulness; SN = subjective norms; PBC = perceived behavioral control; BI = behavioral intention; SE = self-efficacy. All correlations were significant at p<0.001.

Correlation analyses showed that the study constructs were positively interrelated. Behavioral intention was strongly associated with perceived usefulness ($r = 0.731$), perceived ease of use ($r = 0.655$), and trust ($r = 0.637$), and moderately associated with attitudes ($r = 0.522$), perceived behavioral control ($r = 0.510$), S-TIAS ($r = 0.482$), SE ($r = 0.443$), and subjective norms ($r = 0.399$). Perceived usefulness was strongly correlated with perceived ease of use ($r = 0.760$) and moderately correlated with trust ($r = 0.528$), attitudes ($r = 0.478$), perceived behavioral control ($r = 0.459$), S-TIAS ($r = 0.449$), and subjective norms ($r = 0.400$). Trust was moderately to strongly associated with several constructs, including SE ($r = 0.640$), S-TIAS ($r = 0.550$), perceived ease of use ($r = 0.535$), perceived usefulness ($r = 0.528$), subjective norms ($r = 0.515$), perceived behavioral control ($r = 0.404$), and behavioral intention ($r = 0.637$).

Age was positively correlated with subjective norms ($r = 0.232$, $p = 0.003$), trust ($r = 0.151$, $p = 0.049$), and SE ($r = 0.254$, $p < 0.001$), indicating that older participants tended to report higher scores on these constructs.

To further assess whether the main constructs differed across key demographic and survey-administration groups, we conducted independent-samples t-tests by gender and survey language.

Independent-samples t-tests were conducted to examine gender differences across the study constructs (Table 3). No statistically significant gender differences were observed. Male participants had slightly higher mean scores than female participants on S-TIAS, perceived ease of use, perceived usefulness, subjective norms, perceived behavioral control, behavioral intention, attitudes, and trust; however, these differences did not reach statistical significance. The largest differences were observed for perceived ease of use, where males reported somewhat higher scores than females ($p = 0.077$), and S-TIAS ($p = 0.091$).

Table 3
Gender differences in study variables

Scale	**Male** (n=74) M±SD	**Female** (n=96) M±SD	t, p
S-TIAS	4.57±1.30	4.21±1.42	1.70, p=0.091
PEU	5.19±1.30	4.84±1.25	1.78, p=0.077

Table continued

Scale	**Male** (n=74) M±SD	**Female** (n=96) M±SD	t, p
PU	5.24±1.39	5.11±1.34	0.65, p=0.518
SN	3.85±1.56	3.66±1.41	0.82, p=0.414
PBC	5.08±1.44	4.72±1.40	1.65, p=0.101
BI	4.85±1.38	4.77±1.16	0.42, p=0.673
Attitudes	5.26±1.50	5.22±1.38	0.19, p=0.847
Trust	3.91±1.51	3.76±1.17	0.70, p=0.483
SE	2.57±1.00	2.63±0.80	0.44, p=0.657

Note: Values are presented as mean and standard deviation. Group comparisons were conducted using independent-samples t-tests. S-TIAS = short-Trust in Automation Scale; PEU = perceived ease of use; PU = perceived usefulness; SN = subjective norms; PBC = perceived behavioral control; BI = behavioral intention; SE = self-efficacy.

Independent-samples t-tests were also used to compare participants who completed the survey in Russian and Kazakh (Table 4). No statistically significant language-group differences were found for any of the study constructs. Russian-language respondents showed slightly higher mean scores on most scales, including S-TIAS, perceived ease of use, perceived usefulness, behavioral intention, attitudes, trust, and SE; however, all differences were small and non-significant. For example, behavioral intention was slightly higher among Russian-language respondents than Kazakh-language respondents, but this difference was not statistically significant ($p = 0.296$). These findings suggest that the main study constructs were broadly comparable across survey language groups.

Table 4
Survey language differences in study variables

Scale	**Russian** (n=81) M±SD	**Kazakh** (n=89) M±SD	t, p
S-TIAS	4.43±1.21	4.30±1.52	0.61, p=0.543
PEU	5.06±1.09	4.94±1.43	0.64, p=0.525
PU	5.24±1.32	5.10±1.40	0.68, p=0.496
SN	3.76±1.42	3.73±1.52	0.15, p=0.880
PBC	4.94±1.39	4.82±1.46	0.54, p=0.591
BI	4.91±1.14	4.71±1.35	1.05, p=0.296
Attitudes	5.34±1.36	5.14±1.49	0.87, p=0.383
Trust	3.87±1.16	3.78±1.48	0.41, p=0.681
SE	2.64±0.80	2.57±0.98	0.49, p=0.626

Note: Values are presented as mean and standard deviation. Group comparisons were conducted using independent-samples t-tests. S-TIAS = short-Trust in Automation Scale; PEU = perceived ease of use; PU = perceived usefulness; SN = subjective norms; PBC = perceived behavioral control; BI = behavioral intention; SE = self-efficacy.

Because age was associated with several constructs in preliminary analyses, we next examined whether these age-related associations differed by gender or survey language.

Moderation analyses were conducted to examine whether the associations of age with subjective norms, trust, and SE differed by gender or survey language (Table 5, Figure 1). In the gender moderation models, age was a significant positive predictor of subjective norms, trust, and SE. Specifically, older age was associated with higher subjective norms ($\beta = 0.034$, $p < 0.001$), trust ($\beta = 0.020$, $p = 0.028$), and SE (β = 0.021, $p < 0.001$). Gender itself was not a significant predictor in these models, and none of the Age × Gender interaction terms were significant for subjective norms ($p = 0.249$), trust ($p = 0.993$), or SE ($p = 0.446$). These findings indicate that the age-related increase in subjective norms, trust, and SE was broadly comparable for male and female participants.

Table 5
Moderation effects of gender and survey language on the associations between age and subjective norms, trust, and self-efficacy

Scale	Effect	Estimate	SE	p
Social Norms	Age	0.034	0.010	<0.001
	Gender	-0.325	0.221	0.142
	Age * Gender	-0.024	0.020	0.249
SN	Age	0.030	0.001	0.003
	Language	0.032	0.214	0.881
	Age * Language	-0.064	0.020	0.001
Trust	Age	0.020	0.009	0.028
	Gender	-0.223	0.203	0.272
	Age * Gender	0.000	0.019	0.993
Trust	Age	0.017	0.009	0.060
	Language	0.080	0.198	0.686
	Age * Language	-0.049	0.018	0.007
SE	Age	0.021	0.006	<0.001
	Gender	-0.025	0.133	0.853
	Age * Gender	-0.009	0.012	0.446
SE	Age	0.020	0.006	<0.001
	Language	0.058	0.128	0.653
	Age * Language	-0.039	0.012	0.001

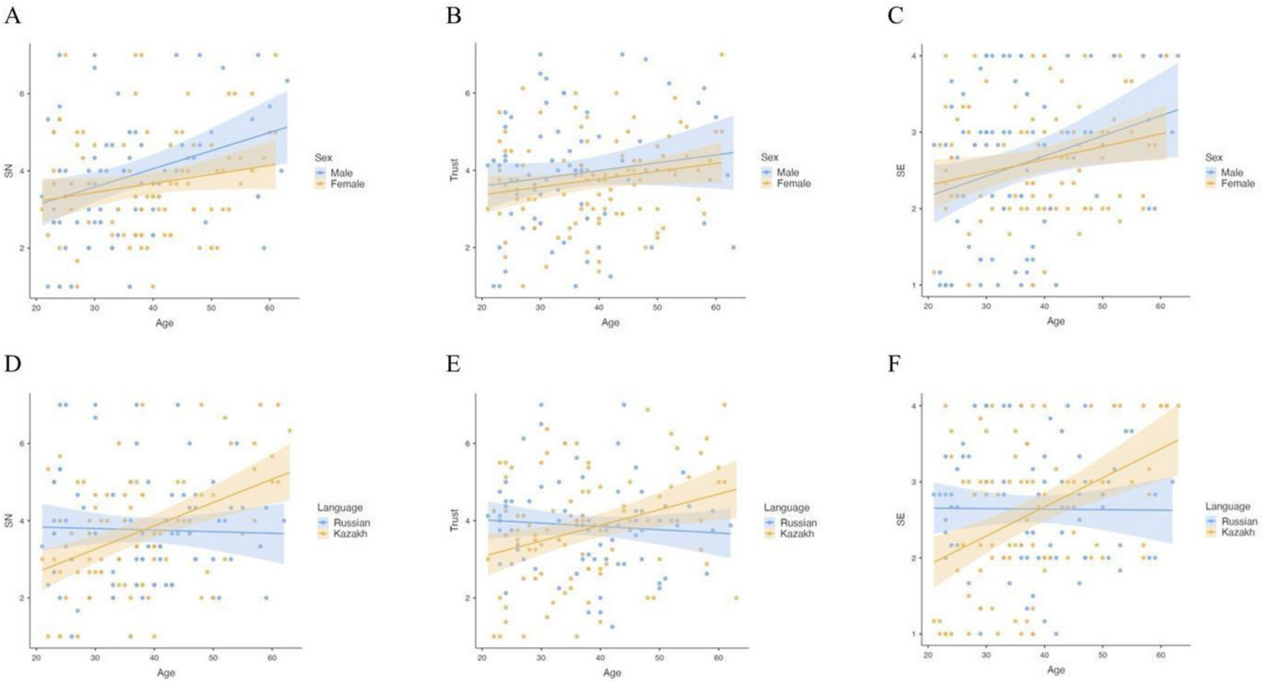
Note: Moderation models examined whether the associations between age and each outcome differed by gender or survey language. Gender was coded as male = 0 and female = 1. Survey language was coded as Kazakh = 0 and Russian = 1. Therefore, the main effect of age in the language moderation models represents the age-related association among Kazakh-language respondents, while the Age × Language interaction indicates the difference in age slopes between Russian- and Kazakh-language respondents. Estimate = unstandardized regression coefficient; SE = standard error; SN = subjective norms; SE outcome = self-efficacy.

Survey language, however, moderated the association between age and all three outcomes. Given that language was coded as Kazakh = 0 and Russian = 1, the main effect of age represents the age-related association among Kazakh-language respondents. Among Kazakh-language respondents, age was positively associated with subjective norms (β = 0.030, $p = 0.003$), trust (β = 0.017, $p = 0.060$), and SE (β = 0.020, $p < 0.001$), although the association with trust was only marginal. The Age × Language interaction was significant for subjective norms (β = -0.064, $p = 0.001$), trust (β = -0.049, $p = 0.007$), and SE (β = -0.039, $p = 0.001$). These negative interaction effects indicate that the positive associations between age and these constructs were weaker among Russian-language respondents than among Kazakh-language respondents. In other words, increases in subjective norms, trust, and SE with age were more pronounced in the Kazakh-language group, whereas these age-related increases were attenuated among Russian-language respondents.

Following these preliminary regression-based moderation analyses, we proceeded to latent-variable modeling. We first evaluated the measurement structure using confirmatory factor analysis before estimating the final structural equation model.

Figure 1

Moderating role of survey language in the associations between age and subjective norms, trust, and self-efficacy



Note: Predicted values are shown separately for Kazakh and Russian language respondents. Survey language was coded as Kazakh = 0 and Russian = 1. Negative Age × Language interaction terms indicate that age-related increases in subjective norms, trust, and self-efficacy were weaker among Russian-language respondents than among Kazakh-language respondents.

A CFA was conducted using WLSMV estimation with THETA parameterization for ordinal indicators. The initial model including SN3 did not produce a fully admissible solution because standard errors could not be computed for the Subjective Norms factor. SN3 was therefore removed. In addition, Trust items T2 and T5 were excluded because they showed substantial local misfit and cross-construct overlap in the revised CFA model. The final nine-factor CFA model included 36 indicators and converged normally. Model fit was acceptable to moderate: $\chi^2(559) = 1202.78$, $p < 0.001$, CFI = 0.948, TLI = 0.942, RMSEA = 0.083 (90% CI 0.077 – 0.089), and SRMR = 0.056. Although RMSEA remained above the threshold for close fit, CFI, TLI, and SRMR supported an acceptable revised measurement structure.

All standardized factor loadings were statistically significant at $p < 0.001$ and generally high. Loadings ranged from 0.918 to 0.969 for trust in automation, 0.746 to 0.899 for perceived ease of use, 0.889 to 0.963 for perceived usefulness, 0.900 for subjective norms, 0.838 to 0.946 for perceived behavioral control, 0.796 to 0.894 for behavioral intention, 0.783 to 0.899 for attitudes, 0.709 to 0.914 for trust in AI, and 0.826 to 0.963 for self-efficacy. Latent correlations were theoretically consistent: behavioral intention was most strongly associated with perceived usefulness ($r = 0.819$), perceived ease of use ($r = 0.752$), and trust ($r = 0.704$), with weaker but significant association with subjective norms ($r = 0.226$). These results support the convergent validity and theoretical coherence of the revised measurement model.

The final ordinal SEM was estimated using WLSMV with THETA parameterization. The model converged normally and demonstrated acceptable overall fit: $\chi^2(574) = 1208.24$, $p < 0.001$, CFI = 0.949, TLI = 0.944, RMSEA = 0.081 (90% CI 0.075 – 0.088), and SRMR = 0.064. All latent constructs were well defined by their indicators, with standardized factor loadings ranging from 0.690 to 0.963 and all loadings statistically significant at $p < 0.001$.

In the structural part of the model, behavioral intention was primarily predicted by perceived usefulness ($\beta = 0.635$, $p < 0.001$), followed by perceived behavioral control ($\beta = 0.343$, $p < 0.001$), trust in

AI (β = 0.334, $p < 0.001$), and attitude (β = 0.157, $p < 0.001$). STIAS showed a significant negative direct association with behavioral intention after controlling for the other predictors (β = -0.364, p = 0.006). Perceived usefulness strongly predicted attitude (β = 0.625, $p < 0.001$), while perceived ease of use was a strong predictor of perceived usefulness (β = 0.669, $p < 0.001$). Trust also positively predicted perceived usefulness (β = 0.243, $p < 0.001$). STIAS was strongly associated with perceived ease of use (β = 0.758, $p < 0.001$) and trust in AI (β = 0.457, $p < 0.001$), while self-efficacy was also a strong predictor of trust in AI (β = 0.516, $p < 0.001$). The model explained 86.1% of the variance in behavioral intention, 67.3% in perceived usefulness, 67.6% in trust in AI, 57.4% in perceived ease of use, and 39.0% in attitude.

Based on the measurement-model findings and theoretical considerations, the final reduced SEM was estimated without the subjective norms factor and retained the constructs most directly contributing to behavioral intention and self-efficacy.

The reduced structural equation model showed acceptable-to-good fit to the data. The chi-square test was statistically significant, $\chi^2(606)$ = 1059.49, $p < 0.001$, which is common in complex models with many categorical indicators. Approximate fit indices supported adequate model fit: RMSEA = 0.067 (90% CI 0.060 – 0.074), CFI = 0.965, TLI = 0.962, and SRMR = 0.063. The measurement model supported the intended latent structure. All factor loadings were statistically significant, and standardized loadings were generally moderate to very high. Standardized factor loadings ranged from 0.784 to 0.896 for STIAS, 0.765 to 0.934 for perceived ease of use, 0.878 to 0.958 for perceived usefulness, 0.732 to 0.830 for perceived behavioral control, 0.781 to 0.898 for behavioral intention, 0.762 to 0.900 for attitude, 0.655 to 0.928 for trust, and 0.833 to 0.964 for self-efficacy (Table 6).

Table 6
Standardized factor loadings of the final measurement model

Latent construct	Indicator	Standardized loading	p
STIAS	STIAS1	0.896	< 0.001
STIAS	STIAS2	0.804	< 0.001
STIAS	STIAS3	0.784	< 0.001
Perceived ease of use	PEU1	0.934	< 0.001
Perceived ease of use	PEU2	0.933	< 0.001
Perceived ease of use	PEU4	0.765	< 0.001
Perceived usefulness	PU1	0.896	< 0.001
Perceived ease of use	PEU2	0.933	< 0.001
Perceived ease of use	PEU4	0.765	< 0.001
Perceived usefulness	PU1	0.896	< 0.001
Perceived usefulness	PU2	0.958	< 0.001
Perceived usefulness	PU3	0.945	< 0.001
Perceived usefulness	PU4	0.878	< 0.001
Perceived behavioral control	PBC1	0.830	< 0.001
Perceived behavioral control	PBC2	0.815	< 0.001
Perceived behavioral control	PBC4	0.732	< 0.001
Behavioral intention	BI1	0.898	< 0.001
Behavioral intention	BI2	0.804	< 0.001
Behavioral intention	BI3	0.876	< 0.001
Behavioral intention	BI4	0.781	< 0.001
Attitude	A1	0.900	< 0.001
Attitude	A2	0.792	< 0.001
Attitude	A4	0.762	< 0.001

Table continued

Latent construct	Indicator	Standardized loading	p
Attitude	A5	0.818	< 0.001
Attitude	A6	0.854	< 0.001
Trust in AI	T1	0.816	< 0.001
Trust in AI	T3	0.928	< 0.001
Trust in AI	T4	0.684	< 0.001
Trust in AI	T6	0.911	< 0.001
Trust in AI	T7	0.910	< 0.001
Trust in AI	T8	0.655	< 0.001
Self-efficacy	SE1	0.833	< 0.001
Self-efficacy	SE2	0.926	< 0.001
Self-efficacy	SE3	0.964	< 0.001
Self-efficacy	SE4	0.949	< 0.001
Self-efficacy	SE5	0.841	< 0.001
Self-efficacy	SE6	0.839	< 0.001

Note: p indicates the statistical significance of the factor loading.

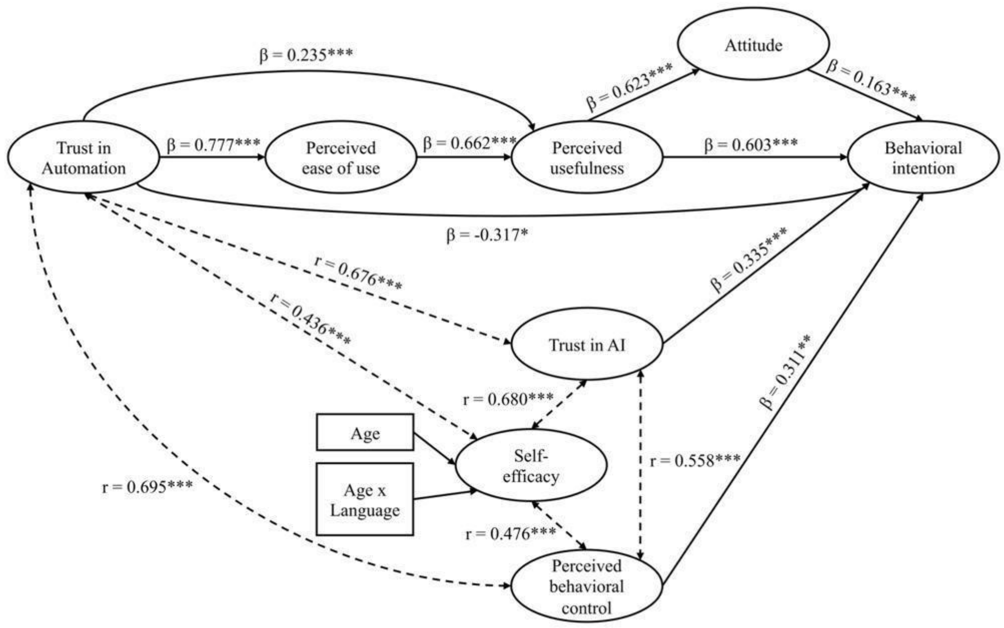
The structural model showed that behavioral intention was strongly explained by the proposed acceptance-related constructs (Table 7, Figure 2). Perceived usefulness was the strongest predictor of behavioral intention, $\beta = 0.603$, $p < 0.001$. Trust also showed a positive association with behavioral intention, $\beta = 0.335$, $p < 0.001$, as did perceived behavioral control, $\beta = 0.311$, $p = 0.001$, and attitude, $\beta = 0.163$, $p < 0.001$. STIAS was negatively associated with behavioral intention, $\beta = -0.317$, $p = 0.010$, indicating that higher STIAS was associated with lower behavioral intention after adjustment for the other predictors. Perceived usefulness was positively predicted by perceived ease of use, $\beta = 0.662$, $p < 0.001$, and trust, $\beta = 0.235$, $p < 0.001$. Attitude was positively predicted by perceived usefulness, $\beta = 0.623$, $p < 0.001$. Perceived ease of use was positively predicted by STIAS, $\beta = 0.777$, $p < 0.001$.

Table 7
Standardized structural path coefficients

Dependent variable	Predictor	β	SE	p
Behavioral intention	Attitude	0.163	0.046	< 0.001
Behavioral intention	Perceived usefulness	0.603	0.083	< 0.001
Behavioral intention	Trust	0.335	0.065	< 0.001
Behavioral intention	STIAS	-0.317	0.123	0.010
Behavioral intention	Perceived behavioral control	0.311	0.096	0.001
Attitude	Perceived usefulness	0.623	0.053	< 0.001
Perceived usefulness	Perceived ease of use	0.662	0.048	< 0.001
Perceived usefulness	Trust	0.235	0.059	< 0.001
Perceived ease of use	STIAS	0.777	0.035	< 0.001
Self-efficacy	Age, centered	0.509	0.098	< 0.001
Self-efficacy	Language	0.009	0.079	0.909
Self-efficacy	Age × Language	-0.352	0.107	0.001

Note: β = standardized structural path coefficient, indicating the direction and magnitude of the relationship between the predictor and the dependent variable; SE = standard error; p = statistical significance level.

Figure 2
Final structural equation model predicting behavioral intention to use AI-based government services



Note: The figure presents the standardized path coefficients from the final structural equation model. Solid arrows indicate statistically significant directional regression paths, while dashed double-headed arrows indicate significant correlations/covariances among latent constructs. Ovals represent latent variables, and rectangles represent observed predictors. Behavioral intention was directly predicted by perceived usefulness, trust in AI, perceived behavioral control, attitude, and trust in automation. Perceived usefulness was predicted by perceived ease of use and trust in automation, and attitude was predicted by perceived usefulness. Self-efficacy was modeled as a parallel outcome predicted by age and the Age × Language interaction and was correlated with trust in automation, trust in AI, and perceived behavioral control.

A significant age-by-language interaction was observed for self-efficacy, $\beta = -0.352$, $p = 0.001$. Simple slope analysis showed that age was positively associated with self-efficacy in the reference language group, Lang = 0, $b = 0.070$, $p < 0.001$. In contrast, the age effect was not statistically significant in the Lang = 1 group, $b = -0.003$, $p = 0.862$. The difference between the two age slopes was significant, $b = -0.073$, $p = 0.003$. These findings indicate that the association between age and self-efficacy differed by language group, with age-related increases in self-efficacy evident only in the reference language group.

The final model explained a large proportion of variance in behavioral intention, $R^2 = 0.847$ (Table 8). It also explained substantial variance in perceived usefulness, $R^2 = 0.657$, and perceived ease of use, $R^2 = 0.603$. The model explained 38.9% of the variance in attitude and 14.5% of the variance in self-efficacy.

Table 8
Explained variance of endogenous latent variables

Endogenous latent variable	R^2	SE	p
Perceived ease of use	0.603	0.054	< 0.001
Perceived usefulness	0.657	0.042	< 0.001
Behavioral intention	0.847	0.054	< 0.001
Attitude	0.389	0.066	< 0.001
Self-efficacy	0.145	0.055	0.009

Note: Statistical significance was set at $p < 0.05$.

Overall, the final reduced SEM supported the proposed acceptance model. Behavioral intention to use AI-based government services was most strongly predicted by perceived usefulness, followed by trust in AI, perceived behavioral control, trust in automation, and attitude. The model also supported an indirect acceptance pathway in which trust in automation predicted perceived ease of use, perceived ease of use and trust in AI predicted perceived usefulness, and perceived usefulness predicted both attitude and behavioral intention. Self-efficacy functioned as a parallel construct rather than a direct determinant of behavioral intention; it was significantly associated with trust-related and control-related constructs and showed an age-related pattern that differed by survey language. The final model explained a substantial proportion of variance in behavioral intention, indicating strong explanatory capacity.

This study examined the psychological, technological, and language-related factors associated with civil servants' behavioral intention to use AI-supported digital government services. Overall, the findings support an integrated psychological model in which technology acceptance is determined by the interaction of cognitive evaluations, trust-related beliefs, and perceived control rather than by technological characteristics alone. The results extend existing technology acceptance research by demonstrating that, in the context of Kazakhstan's public administration, behavioral intention emerges from the combined influence of perceived usefulness, trust in AI, perceived behavioral control, and attitudes toward AI. Furthermore, the moderating role of language suggests that psychological determinants of AI acceptance should be interpreted within their broader sociocultural context rather than as universal individual characteristics.

Among the examined predictors, perceived usefulness emerged as the strongest determinant of behavioral intention. This finding suggests that civil servants evaluate AI primarily through an instrumental cognitive framework. Unlike consumers or voluntary users, public officials operate within institutional environments characterized by procedural accountability, regulatory compliance, and responsibility for administrative decisions. Consequently, AI is not primarily perceived as an innovative technology but as a professional instrument capable of improving work performance, reducing routine administrative burden, and facilitating evidence-based decision-making. In this context, perceived usefulness functions as a psychological justification for adopting AI, allowing employees to reconcile innovation with professional responsibility. This interpretation is consistent with the findings of Ahn and Chen (2022), who demonstrated that civil servants evaluate AI more positively when it is associated with reducing administrative workload, and with Rathnayake et al. (2025), who identified perceived usefulness as the strongest predictor of technology adoption in the public sector. Therefore, practical implementation strategies should focus less on promoting AI as an innovative technology and more on demonstrating its tangible contribution to everyday administrative tasks.

Trust in AI also played a central role in explaining behavioral intention. Beyond its direct influence on AI acceptance, trust significantly contributed to perceived usefulness, indicating that psychological trust precedes cognitive evaluations of technological value. This finding supports the view that trust functions as a mechanism for reducing uncertainty associated with algorithmic decision-making. When civil servants perceive AI systems as reliable, predictable, and competent, they allocate fewer cognitive resources to monitoring potential errors and become more willing to recognize the practical value of AI-supported recommendations. This interpretation is consistent with the meta-analysis by Kaplan et al. (2023), which identified trust as a robust determinant of both technology evaluation and behavioral intention across different contexts. Similarly, Kasilingam (2020) argued that institutional trust can be transferred to emerging technologies before direct interaction with the system occurs. The relatively low average level of trust observed in the present study, despite its strong predictive value, further suggests that trust remains a modifiable psychological resource rather than a stable characteristic. Consequently, strengthening institutional confidence, transparency, and explainability may substantially improve AI acceptance within public administration.

The observed associations between trust, perceived behavioral control, self-efficacy, and trust in automation further indicate that trust should not be understood as an isolated psychological construct. Instead, it appears to represent one component of a broader psychological resource system supporting technology acceptance. Individuals who trust AI also tend to perceive themselves as more capable of using digital technologies, report greater confidence in organizational support, and demonstrate a stronger willingness to interact with automated systems. This finding is consistent with Kelly et al. (2023), who conceptualized trust in AI as a multidimensional construct shaped simultaneously by cognitive beliefs, affective responses, and organizational conditions. Within Kazakhstan's public sector, where digital government services already enjoy relatively high public acceptance (Kusherbayev & Dulambayeva, 2025), this psychological resource system may facilitate the gradual transfer of institutional trust toward AI-based technologies.

Perceived behavioral control also emerged as an independent predictor of behavioral intention, supporting the assumptions of the Theory of Planned Behavior (Ajzen, 1991). From a psychological perspective, perceived behavioral control reflects not only objective access to technological resources but also individuals' subjective sense of agency–the belief that they possess sufficient opportunities, support, and capability to successfully integrate AI into their professional activities. In public organizations, where implementation of new technologies often depends on organizational regulations, managerial support, and technical infrastructure, employees may evaluate AI adoption through both personal and environmental considerations. Therefore, perceived behavioral control represents the psychological interface between individual competence and institutional readiness. This interpretation is particularly relevant for Kazakhstan, where substantial infrastructural differences between metropolitan and regional government institutions remain evident (Kogabayev & Banerjee, 2024). The findings therefore suggest that strengthening psychological readiness for AI requires not only developing employees' competencies but also creating organizational environments that reinforce perceptions of control over technology use.

Self-efficacy (SE), contrary to expectations, did not demonstrate a direct effect on behavioral intention in the final structural model. Although this finding differs from studies reporting self-efficacy as one of the strongest predictors of AI adoption (Du & Li, 2026) and from the mediation pathway proposed by Li et al. (2024), it provides important insights into the psychological mechanisms underlying AI acceptance in public administration. Rather than functioning as an immediate determinant of behavioral intention, self-efficacy appears to operate as a foundational psychological resource that supports other cognitive and motivational processes involved in technology acceptance. In highly regulated organizational environments, such as the public sector, confidence in one's own abilities alone may be insufficient to motivate technology use if employees do not simultaneously perceive organizational support, trust the technology, or believe that they have sufficient control over its implementation.

This interpretation is supported by the strong covariance observed between self-efficacy, perceived behavioral control (PBC), trust in AI (TRUST), and trust in automation (S-TIAS). Together, these constructs appear to represent an interconnected system of psychological resources that facilitates adaptation to technological change. Individuals who are confident in their own abilities are also more likely to perceive greater control over AI implementation and to develop stronger trust in intelligent systems. Consequently, self-efficacy contributes indirectly to AI acceptance by reinforcing psychological conditions that enable technology use rather than by directly determining behavioral intention itself. Furthermore, self-efficacy was predicted by the interaction between age and language, suggesting that beliefs about one's technological competence are shaped not only by individual characteristics but also by broader sociocultural and linguistic contexts. This interpretation is consistent with the conceptualization of self-efficacy proposed by Compeau and Higgins (1995), who argued that self-efficacy functions as a fundamental psychological resource through which demographic and contextual factors influence technology-related behavior.

The significant relationship between perceived usefulness (PU) and attitude toward AI (ATT) confirms one of the central assumptions of the Technology Acceptance Model, namely that cognitive evaluations of technology precede affective responses. However, beyond supporting TAM, this finding also highlights an important psychological mechanism underlying AI acceptance. When civil servants perceive AI as genuinely improving work efficiency, reducing routine administrative burden, and supporting more accurate decision-making, these cognitive evaluations become internalized as favorable emotional attitudes toward the technology. Thus, positive attitudes do not emerge independently but develop through repeated cognitive appraisal of AI's practical value in everyday professional activities. This finding suggests that attitudes toward AI are not merely emotional reactions but are grounded in employees' accumulated experiences and beliefs regarding the technology's usefulness.

The independent contribution of attitude to behavioral intention further indicates that AI acceptance cannot be explained solely by rational evaluations of technological benefits. Even after accounting for perceived usefulness, employees' emotional appraisal of AI continued to influence their willingness to adopt the technology. This finding supports psychological perspectives emphasizing that technology acceptance results from the interaction of cognitive and affective processes rather than from cognitive evaluations alone. The persistence of this relationship is consistent with the findings of Rózsa et al. (2025), who reported that positive attitudes toward AI remained a significant predictor of technology use even after controlling for prior experience. Within the Kazakhstani public sector, this finding has particular practical relevance. Skepticism toward algorithmic decision-making reported in previous studies (Bokayev et al., 2021) appears to represent not merely a knowledge deficit but an affective psychological barrier. Consequently, successful AI implementation should combine technical training with interventions aimed at strengthening positive perceptions of AI, increasing transparency, and reducing uncertainty surrounding algorithm-assisted decision-making.

The role of trust in automation (S-TIAS) proved to be more complex than initially expected, reflecting the multidimensional nature of trust in intelligent systems. On the one hand, trust in automation was positively associated with perceived ease of use, suggesting that confidence in automated systems reduces the cognitive effort required to interact with new technologies. When employees perceive AI systems as reliable and predictable, they are less likely to anticipate difficulties during use, making the technology appear easier to operate. This psychological mechanism is consistent with Rathnayake et al. (2025), who argued that trust reduces the perceived cognitive costs associated with technology adoption. Consequently, trust contributes indirectly to behavioral intention by facilitating favorable cognitive evaluations of AI before actual use occurs.

The direct negative association between trust in automation (S-TIAS) and behavioral intention presents an important theoretical insight into the complex psychological nature of trust. At first glance, this finding appears counterintuitive because trust is generally regarded as a facilitator of technology acceptance. However, within public administration, where civil servants remain personally accountable for administrative decisions, excessive reliance on automated systems may evoke concerns regarding professional responsibility, loss of control, and overdependence on algorithmic recommendations. From this perspective, trust in automation should not be viewed as a uniformly beneficial construct. Instead, it appears to reflect a balance between confidence in technological capabilities and awareness of the potential risks associated with delegating decision-making authority to AI systems. This interpretation is consistent with the conceptual framework proposed by Lee and See (2004), who argued that excessive trust may encourage automation complacency and reduce critical monitoring of system outputs. Similarly, Alon-Barkat and Busuioc (2022) demonstrated that higher trust in automated decision-making may increase susceptibility to automation bias. Consequently, the present findings suggest that trust in automation exerts both facilitating and constraining psychological influences on AI acceptance. While trust lowers cognitive barriers to interacting with AI by increasing perceived ease of use, excessive generalized trust may simultaneously reduce willingness to adopt AI in contexts where professional accountability requires continuous human oversight. These findings emphasize that effective AI implementation in government institutions should promote calibrated rather than unconditional trust in intelligent systems.

The significant interaction between age and questionnaire language provides further evidence that AI acceptance is shaped not only by individual psychological characteristics but also by the sociocultural environment in which technology is introduced. Among Kazakh-speaking respondents, older civil servants demonstrated greater confidence in their ability to use AI, whereas no comparable relationship was observed among Russian-speaking participants. Rather than reflecting differences in technological competence, this pattern suggests that self-efficacy develops through the interaction between personal experience and contextual conditions, including language environment and accessibility of digital resources. In multilingual public organizations, language functions not merely as a communication tool but also as a cognitive resource influencing how individuals perceive their own technological competence.

This interpretation is supported by Cognitive Load Theory (Sweller, 2011), according to which interacting with technology in a linguistically demanding environment requires additional cognitive resources that may reduce confidence in successful task performance. At the same time, the Adaptive Control Hypothesis (Green & Abutalebi, 2013) proposes that bilingual individuals develop greater cognitive flexibility through continuous language switching. The present findings suggest that these mechanisms may operate simultaneously within public administration. Language appears to influence AI acceptance not because one language group possesses greater technological ability, but because the linguistic context determines the amount of cognitive effort required to interact with AI systems. Similar conclusions were reported by Hou et al. (2026), who identified language proficiency as an important moderator of AI adoption, and by Caputo et al. (2025), who emphasized that age-related differences in technology acceptance largely depend on contextual and organizational factors rather than chronological age itself.

The practical implications of these findings extend beyond technology implementation and highlight the importance of psychologically informed digital transformation strategies. The dominant influence of perceived usefulness indicates that civil servants are unlikely to adopt AI solely because it represents an innovative technology. Instead, acceptance develops when employees clearly recognize how AI improves everyday work performance, supports administrative decision-making, and reduces routine workload. Consequently, implementation strategies should prioritize demonstrations of concrete workplace benefits rather than generalized digital literacy campaigns. As suggested by Ahn and Chen (2022), pilot projects that visibly reduce administrative burden are substantially more effective in promoting AI acceptance than abstract organizational narratives about innovation.

The significant contribution of perceived behavioral control, together with its close relationship with self-efficacy and trust, further indicates that psychological readiness for AI cannot be separated from organizational readiness. Employees' willingness to use AI depends not only on their confidence and motivation but also on whether the organizational environment enables successful technology use through adequate infrastructure, managerial support, and opportunities for learning. This finding reinforces the argument of Neumann et al. (2024) that technological infrastructure and psychological readiness operate as complementary rather than independent determinants of technology adoption. Therefore, interventions aimed exclusively at increasing digital competencies without addressing institutional barriers are unlikely to achieve sustainable implementation outcomes.

The moderating role of language also has important implications for AI training within multilingual public organizations. Rather than providing standardized educational programs, AI literacy initiatives should account for differences in cognitive demands associated with language use. In accordance with Sweller's (2011) recommendations, reducing unnecessary cognitive load through intuitive interface design, gradual introduction of AI functionalities, and high-quality multilingual support may strengthen employees' confidence and facilitate technology adoption. During the ongoing localization of AI services in Kazakhstan, maintaining equally comprehensive Kazakh- and Russian-language interfaces may therefore represent not only a technical requirement but also a psychological strategy for reducing disparities in self-efficacy across language groups.

Finally, the coexistence of positive indirect and negative direct effects of trust in automation suggests that successful AI governance requires balancing confidence with critical reflection. Encouraging unquestioning reliance on algorithmic recommendations may unintentionally increase automation bias, whereas excessive skepticism may hinder technological innovation. The present findings therefore support approaches to responsible AI implementation that promote calibrated trust through transparency, explainability, and meaningful human oversight. In particular, explainable AI (XAI) may strengthen appropriate trust by enabling civil servants to understand, evaluate, and critically interpret algorithmic recommendations rather than simply accepting or rejecting them, as suggested by Shin and Park (2019). Such psychologically informed governance strategies may ultimately facilitate sustainable AI adoption while preserving professional responsibility and human agency in public administration.

The study has several methodological strengths. First, the use of the WLSMV estimator with THETA parameterization and a probit link function ensured appropriate estimation of ordinal indicators and latent variables, providing more robust parameter estimates than conventional maximum likelihood procedures under non-normal distributions. Second, to our knowledge, this is one of the first studies to investigate AI acceptance among civil servants in Kazakhstan, thereby extending psychological research on technology acceptance to an understudied public-sector context in Central Asia. Third, the inclusion of the Age × Language interaction as a theoretically grounded moderator contributes to existing technology acceptance research by introducing a sociolinguistic perspective that has received limited attention within TAM- and UTAUT-based studies.

Several limitations should be considered when interpreting the findings. First, the sample was recruited using convenience sampling with elements of purposive selection. Although this approach is common in organizational psychology, where access to professional populations is restricted by institutional procedures, it may have introduced selection bias. Civil servants who agreed to participate may have been more interested in digital technologies or more willing to express their opinions about AI than those who declined participation. Consequently, the sample cannot be considered fully representative of the entire population of civil servants in Kazakhstan.

Second, although participants were recruited from both central and regional executive bodies, the sample size (n = 170) and the predominance of respondents from the capital region limit the generalizability of the findings. Kazakhstan's civil service comprises more than 90,000 employees working across organizations that differ substantially in digital infrastructure, organizational culture, and access to technological resources. Therefore, the observed psychological relationships should be interpreted with caution when extending the findings to all levels of public administration.

Third, the cross-sectional design allows theoretically informed associations among latent constructs to be examined but does not permit conclusions regarding causal relationships or the temporal ordering of psychological processes. Technology acceptance is dynamic and may change as employees gain experience with AI systems. Future longitudinal studies are needed to examine how perceived usefulness, trust, self-efficacy, and behavioral intention evolve throughout different stages of AI implementation.

Fourth, all constructs were assessed using self-report questionnaires administered within a single data collection procedure. Although validated psychometric instruments were used, self-report measures remain vulnerable to common method variance, social desirability bias, and respondents' subjective perceptions. In organizational settings, particularly within the public sector, participants may also provide responses that reflect perceived institutional expectations regarding digital transformation rather than their actual attitudes or future behavior. Future studies would benefit from combining self-report data with behavioral indicators of AI use, supervisor assessments, or objective organizational measures.

Finally, the language group was operationalized as a dichotomous variable (Kazakh vs. Russian), which simplified the multilingual reality of Kazakhstan's public administration. Many civil servants are functionally bilingual and use both languages in different professional contexts. Future research should therefore employ more refined measures of language proficiency, language preference, and frequency of language use to better understand how sociolinguistic factors influence AI acceptance.

Conclusion

This study provides evidence that civil servants' intention to use digital government technologies is shaped by a combination of instrumental, psychological, and contextual factors. In the final structural equation model, perceived usefulness emerged as the strongest direct predictor of behavioral intention, indicating that civil servants are more likely to intend to use such technologies when they perceive them as practically valuable for their work. Trust, perceived behavioral control, attitude, and STIAS also contributed significantly to behavioral intention, suggesting that adoption readiness depends not only on perceived benefits, but also on confidence in the system, perceived feasibility of use, and individual psychological responses to technology.

The findings further suggest that perceived ease of use operates mainly through perceived usefulness, highlighting the importance of user-friendly design and practical training. Technologies that are easier to understand and operate may be more readily perceived as useful, which in turn can strengthen positive attitudes and behavioral intentions. Trust also appears to play a central role, both as a direct predictor of intention and as a factor associated with perceived usefulness, emphasizing the need for transparency, reliability, and institutional legitimacy in the implementation of digital government systems.

Self-efficacy was not a direct predictor of behavioral intention in the final reduced model, but it remained meaningfully connected to other constructs, including trust, perceived behavioral control, and STIAS. In addition, the significant Age × Language interaction showed that the association between age and self-efficacy differed by language group. This finding suggests that confidence in using digital government technologies may be shaped by linguistic, educational, or sociocultural context, and that uniform implementation strategies may not be equally effective for all groups of civil servants.

Overall, the results indicate that successful digital transformation in public administration requires more than technological deployment. Civil servants need to clearly see the practical usefulness of digital tools, trust their reliability and institutional purpose, feel that they have sufficient control and support to use them, and receive training that is sensitive to language and contextual differences. Future studies should examine whether these factors predict actual technology use over time and should further explore how language-sensitive and trust-building interventions can strengthen technology acceptance in government settings.

Funding

This study was funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. AP26198635 “Social perceptions of Kazakhstani society about the development of artificial intelligence: trust and fears”).

Author Contributions

Abdykalikova Marta:Methodology, Supervision, Project administration.

Kaldybayev Timur: Investigation,Writing.

Bolatov Aidos: Data curation, Formal Analysis.

Bozymbayeva Nazym: Writing – Review & Editing.

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Information about the authors:

Abdykalikova Marta – Candidate of Psychological Sciences, associated professor, L.N. Gumilyov Eurasian National University (Astana, Kazakhstan, e-mail: martadaria2019@gmail.com).

Kaldybayev Timur – MBA, Lecturer at the Graduate School of Business, Almaty Management University (Almaty, Kazakhstan, e-mail: timqaldy@gmail.com).

Bolatov Aidos – M.D. – researcher at Eurasian National University, Astana, Kazakhstan; PhD candidate at Shenzhen University (Shenzhen, China, e-mail: bolatovaidos@gmail.com).

Bozymbayeva Nazym (corresponding-author) – MSSc in Counselling Psychology, lecturer at Maqsut Narikbayev University, Astana, Kazakhstan, researcher at Eurasian National University (Astana, Kazakhstan, e-mail: nbozymbaeva@gmail.com).

Авторлар туралы мәлімет:

Абдықалықова Марта – психология ғылымдарының кандидаты, қауымдастырылған профессор, Л.Н. Гумилев атындағы Еуразия ұлттық университеті (Астана, Қазақстан, e-mail: martadaria2019@gmail.com).

Қалдыбаев Тимур – MBA, жоғары бизнес мектебінің оқытушысы, Almaty Management University (Алматы, Қазақстан, e-mail: timqaldy@gmail.com).

Болатов Айдос – медицина ғылымдарының докторы (M.D.), Л.Н. Гумилев атындағы Еуразия ұлттық университетінің зерттеушісі; Шэньчжэнь университетінің PhD докторанты (Шэньчжэнь, Қытай, e-mail: bolatovaidos@gmail.com).

Бозымбаева Назым (корреспонденттік автор) – кеңес беру психологиясы саласындағы әлеуметтік ғылымдар магистрі, Maqsut Narikbayev University оқытушысы; Л.Н. Гумилев атындағы Еуразия ұлттық университетінің зерттеушісі (Астана, Қазақстан, e-mail: nbozymbaeva@gmail.com).

Сведения об авторах:

Абдыкаликова Марта – кандидат психологических наук, ассоциированный профессор, Евразийский национальный университет имени Л.Н. Гумилёва (Астана, Казахстан, e-mail: martadaria2019@gmail.com).

Калдыбаев Тимур – MBA, преподаватель Высшей школы бизнеса, Almaty Management University (Алматы, Казахстан, e-mail: timqaldy@gmail.com).

Болатов Айдос – доктор медицины (M.D.), исследователь Евразийского национального университета (Астана, Казахстан); PhD-докторант Shenzhen University (Шэньчжэнь, Китай, e-mail: bolatovaidos@gmail.com).

Бозымбаева Назым (автор-корреспондент) – магистр социальных наук в области консультативной психологии, преподаватель Maqsut Narikbayev University; исследователь, Евразийский национальный университет имени Л.Н. Гумилёва (Астана, Казахстан, e-mail: nbozymbaeva@gmail.com).

Received: June 19, 2026
Accepted: August 28, 2026