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TRUST IN GOVERNMENT AND SUPPORT FOR AI IN
PUBLIC SERVICES: EVIDENCE FROM AN EXPERIMENT

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САЛАСЫНДАҒЫ ЖИ-ТІ ҚОЛДАУ: ЭКСПЕРИМЕНТ НӘТИЖЕЛЕРІ

ДОВЕРИЕ К ПРАВИТЕЛЬСТВУ И ПОДДЕРЖКА ИИ В СФЕРЕ
ГОСУДАРСТВЕННЫХ УСЛУГ: РЕЗУЛЬТАТЫ ЭКСПЕРИМЕНТА

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**TRUST IN GOVERNMENT AND SUPPORT FOR AI IN
PUBLIC SERVICES: EVIDENCE FROM AN EXPERIMENT**

by Amina Kosbayeva

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ABSTRACT

The increased introduction of Artificial Intelligence (AI) tools in governance raises questions about the conditions under which citizens are willing to accept their implementation. This thesis particularly explores how dimensions of trust in government shape the support for AI in public services.

The conducted analysis is grounded in the multidimensional understanding of trust in government. To conceptualize the notion, dimensions of perceived competence and perceived benevolence are distinguished and utilized as independent variables in the testing process. Based on this theoretical framework, the study hypothesized that both dimensions independently and positively shape the support for AI in the public sector; and the two dimensions enter a conditional relationship in such a way that when perceived benevolence is absent, the presence of perceived competence will not lead to support for AI.

To empirically test these hypotheses the study employs a survey-based experimental design, structured to expose the respondents to treatments with varying information about governmental competence and benevolence. The analysis of data revealed an absence of positive associations between perceived competence and support for AI. Perceived benevolence and interaction term coefficients were found to be heading in the expected direction, even though none of the hypotheses could be considered as supported due to the insignificance of observed effects. Notably, however, the study found two control variables - general attitudes toward AI and baseline trust in government - as strong and consistent predictors of support for AI in the public sector. These insights of the study carry implications for future research and policymaking, emphasizing that trust in government should be treated as one of the key factors that influences the acceptance and successful implementation of AI-driven technology in the public service delivery.

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Chapter 1: Introduction

1.1. Overview of the study

Artificial Intelligence (AI) has increasingly become a primary area of innovation in public administration, reshaping how governing structures design, implement, and evaluate public services. AI technologies are now commonly used for predictive analysis in social welfare programs, resource allocation, and urban planning. Moreover, AI-based algorithms are frequently employed to provide recommendations to public decision-makers and government workers (Schnell & Schmidt-Scheele, 2025). Such growing use of AI reflects an important shift toward algorithmic governance, in which administrative tasks are partially delegated to data-driven systems.

AI's extensive involvement in the public service provision makes it important to address questions about trust in AI technologies and the institutions integrating them. Citizens are not only asked to trust governmental institutions, but also technological systems that those institutions deploy. As a result, a layered trust relationship is formed. People are tasked with both evaluating the intentions and capabilities of the state, as well as the reliability and safety of AI tools. While it may seem rather intuitive that people's perceptions of AI technologies in public service provision become intertwined with their perceptions of the government itself, there remains a notable lack of scholarly inquiry into this relationship. Existing research has predominantly examined public trust in government or their acceptance of AI in isolation, thus leaving the interaction between the trust in government and support for AI unexplored.

Consequently, the current state of research can be characterized by the presence of a certain critical gap. If AI becomes a more of an integral instrument in carrying out public services, citizens' perceptions of the state's competence and benevolence may shape their willingness to support the implementation of AI systems in governance. In turn, skepticism

toward the government may foster resistance towards algorithm-driven systems. Therefore, understanding this relationship stands out as an essential area of interest in not only the political science field, but the policymaking area as well.

It is worth mentioning that the topic of the given study is relevant in both practical and theoretical aspects. With AI tools being actively introduced by governments around the world, it is necessary to address concerns regarding the legitimacy of such initiatives to ensure that regulatory frameworks take into account broader public attitudes. Speaking more normatively, the use of AI does raise important questions about accountability, transparency, and scope of government control. Moreover, if citizens' support for AI is shaped by the levels of trust in government, then it may result in uneven acceptance of new technology in public services and reinforcement of existing political divides.

1.2. Research question and theoretical arguments

With the above mentioned in mind, this study aims at answering the following research question: "What effect do perceptions of governmental competence and benevolence have on citizens' support for AI in public services?". The conducted analysis is grounded in a theoretical framework that conceptualizes trust as a multidimensional construct, which is composed of perceived competence and benevolence. Competence in this context refers to the technical expertise, administrative capacity, and professionalism of the government in policy design and implementation, while benevolence reflects the genuine motivation of the state to act in the interest of the public as perceived by citizens. These dimensions are expected to shape how people evaluate institutions and their initiatives.

In this study support for AI in the public sector is treated as not being solely driven by individual attitudes toward technology, but by pre-existing beliefs about the government. In such a context, when citizens perceive the government as competent, they are more likely to

accept an understanding that AI tools in public services will be implemented effectively and produce desirable outcomes. In the same manner, when the government is perceived as benevolent, people may be more inclined to believe that AI will be used ethically and in ways that serve the interests of the society.

In accordance with this logic, this study puts forward three core expectations. Firstly, when the government is perceived as competent, there will be observable support for AI in public services amongst the citizens. Secondly, when the government is perceived as benevolent, people will support the implementation of AI in public services. Thirdly, it is noted that the two dimensions of trust do not necessarily operate in isolation, but they rather enter a conditional relationship in the following manner: in the absence of perceived benevolence of the state, the presence of perceived competence will not lead to support for AI.

1.3. Structure of the thesis

This thesis is organized as follows. Chapter 2 reviews the relevant literature on the use of AI in the public sector and factors that shape trust in algorithm-driven technology in governance. The analysis of contemporary works highlights the key gap, characterized as the limited integration of institutional trust framework in the assessment of what drives the support for AI in the public sector. To bridge this gap, Chapter 3 develops the theoretical foundation by conceptualizing trust in government as a multidimensional notion and forms testable hypotheses regarding the effects of institutional trust dimensions on support for AI in public services.

Chapter 4 outlines the research design and methodology, explaining the choice of survey experiment, detailing the data collection process, as well as operationalization and measurement of variables and relationships. Chapter 5 presents the results of the testing and

provides descriptive statistics, regression models, robustness checks, and treatment groups analyses. Chapter 6 interprets the presented findings and places them within the theoretical framework, assessing whether the data supports the presented hypotheses. Theoretical, substantive, policy implications, and limitations are also thoroughly addressed. Finally, Chapter 7 concludes the thesis and summarizes the main contributions of this study, as well as reflecting on the significance of the research and potential avenues for further scholarly work.

Chapter 2: Literature Review

2.1. Introduction

The governments around the world are actively introducing AI-driven technologies in various areas of the public sector (Susar and Aquaro, 2019). Such systems are integrated in administrative processes, service delivery, and decision-making. But successful deployment of AI in public services can not be realized without the citizens' support for these initiatives. Therefore, understanding which factors shape public acceptance is an important subject matter both for policymakers and researchers in different scientific fields.

This chapter focuses on the existing literature regarding the use of AI in the public sector, as well as the citizens' perceptions and evaluations of algorithm-driven tools. With AI being a relatively new technology itself, the scholarship on the topic can be characterized as recent. The earlier research has focused extensively on the technical capabilities of AI, while contemporary works highlight the importance of social and institutional factors that might drive public support for AI. Particular attention in this chapter is paid to scholarly works that explain which phenomena influence people's trust in AI-driven technology in the public sector.

This literature review chapter begins by conceptualizing AI in the context of governance, outlining the key domains of its application. Next, the chapter provides an analysis of benefits associated with AI adoption, which include increased efficiency of public services, improved service delivery, enhanced policymaking and evidence-gathering. Additionally, risks associated with the use of AI are discussed, highlighting features of bias, lack of transparency, and accountability concerns. This overview enables to establish a wider socio-political context within which public attitudes toward AI are formed.

The literature review also contains assessment of the notion of trust as a central determinant of AI acceptance. An emphasis is made on the nature of AI in the public sector as

a socially embedded notion. From there, the conceptualizations of trust in AI as human-like and functionality-based dimensions, as well as task type and user experience factors are included to define the established approaches to the study of public perceptions of AI systems. This examination is followed by identifying limitations in the existing literature. Notably, the trust in government which is deploying AI or aims at doing so has been found to not be sufficiently paid attention to.

2.2. The use of AI in the public sector

Scholars have identified the three principal domains of AI application in the public sector: automated decision making systems, conversational chatbots, and security tools. Automated decision-making systems allow governments to detect complex patterns, classify populations by risk or need, and predict future outcomes, thus improving efficiency in areas such as welfare distribution, healthcare, and policing (Wirtz et al., 2019; De Sousa et al., 2019; Henman, 2020). Chatbots serve as digital interfaces, which strengthen citizen engagement and administrative productivity by handling routine requests (Wirtz et al., 2019; Aoki, 2020; Henman, 2020). AI security tools support the regulatory enforcement, cybersecurity, and crisis management by detecting fraud, prediction of threats, and analysis of disinformation (Wirtz et al., 2019; Henman, 2020).

Another conceptualization is provided by De Sousa et al. (2019), who describe AI in public services as an ecosystem of techniques (e.g. machine learning, artificial neural networks, fuzzy logic, multi-agent systems) aimed at solving administrative, environmental, and social issues. Hence, similarly to Henman (2020), De Sousa et al. (2019) do not treat AI tools as a single technology. Such an approach adequately fits into the policy-oriented framework, which emphasizes the interconnectedness of AI development, policy implementation, and social acceptance. Such approach broadens the understanding of AI in

governance by characterizing the technology not merely as a neutral instrument, but as a socially embedded process that is shaped by the state's institutional capacity and public perception.

Mergel et al. (2024) distinguish three different dimensions of AI implementation in public administration based on the new structural forms in which technology is tested and experimented with. The first dimension is a technology-deterministic dimension and it reflects the development of AI in an isolated laboratory environment outside of practical administration. The set up of AI tools is not problem-centric as the development is perceived to be driven by the availability and ability of such technology to assist in some administrative processes. The second dimension - data-induced decision-making - is focused on the usage of AI potential to process large amounts of data to generate policy proposals. This dimension is driven by an understanding that AI may presumably make more rational decisions based on bigger amounts of data than what humans are capable of analyzing. The third dimension refers to the organisational transformation dimension and focuses on areas of administrative work in government that can be improved by AI.

Madupati (2024) identifies four core areas of AI that are used to increase efficacy and precision of the government. They include Natural Language Processing, Machine Learning, Computer Vision, and Robotic Process Automation. The primary functions of such areas of AI are to enhance the interaction between government organizations and citizens, forecast future events based on the analysis of large amounts of data, automate routine bureaucratic processes, and increase public safety by using AI-powered surveillance. The latter implementation is imperative to this study because it uses the example of the Kazakhstan's government's implementation of AI-powered traffic and mobility platform "Sergek".

The platform was developed as a part of the broader "Smart City" concept that went in line with the rapid government digitalization process (Gritsenko et al., 2025). The technology

was positively accepted by the police and its introduction was perceived as a way to facilitate crime prevention, solve cases and manage subordinates. However, the “Sergek” did not affect the rate of corruption or police efficiency, therefore not meeting expectations of those citizens who considered the innovation as a solution to mentioned issues (Slade et al., 2022). The technological nature of the tool was actually used by the policeman as an explanation for missing footage that could be used as evidence in court cases (Gritsenko et al., 2025).

2.3. Benefits and risks of AI usage in the public sector

The overview of the key areas of AI use in the public sector shows that algorithm-driven tools are currently used by the governments to support and assist the work of human workers rather than outright replacing them. However, it is also evident that implementation of AI is directly linked to the capabilities of AI, meaning that the governments are ready to use the system’s full potential in realizing public services. Based on that, it is valid to expect that the use of AI in governance will expand and transform as the AI technology itself develops.

Proponents of the AI being used in governance argue that the integration of such technologies increases the efficiency, transparency, and evidence-based policymaking by offering governments the means to more effectively respond to the various issues (Henman, 2020). However, the growing reliance on algorithmic systems also raises various ethical and political questions. In particular, researchers in the field have noted the following shortcoming of the new technologies: while AI can optimize administrative decisions, it simultaneously can challenge the accountability and fairness of the governing systems, as well as influencing the level of public trust (Vereschak et al., 2024). The mentioned risks are especially dangerous in the context of AI-assisted decision making.

Henman (2020) identifies four key risks associated with the application of AI in public administration: bias and discrimination, legality and due process, accountability and explainability, and power and control. Addressing these concerns necessitates the development of technological safeguards, which would be characterized by the establishment of institutional mechanisms, stronger legal frameworks, and independent oversight systems (Henman, 2020). Furthermore, it is essential that AI tools used in public administration are designed to be explainable and fair, ensuring the public clearly understands how these systems operate and are implemented (De Sousa et al., 2019; Henman, 2020).

2.4. Trust as a determinant of support for AI

There is a vital factor missing in the earlier mentioned analysis that drives the social acceptance of AI technologies in government, which is trust. Scholars have widely referred to trust as a pivotal determinant of the public's willingness to adopt and rely on AI technologies (Choung et al., 2023; Thiebes et al. 2020). In particular, they argue that the gradually autonomous, opaque, and human-like nature of AI makes trust a crucial social and psychological mechanism through which people manage uncertainty and perceived risk.

Findings of Haesevoets et al. (2024) reveal that people are not entirely against the deployment of AI in the public sector. Through conducting three observational studies researchers found that people preferred AI to have considerably less decision-making weight than human experts. There was more sympathy toward AI tools being used to provide input and advice to human decision-makers and, generally, AI's involvement in the public sector was perceived as more suitable for low ideologically-charged decisions. These observations highlight the importance of the above-mentioned assessment of AI in the public sector with regards to socio-political contexts in which the technology is planned to be deployed. Moreover, the findings suggest that exploring the effect of trust in government on AI

acceptance in the public sector is necessary as people's perceptions were found to be placing an emphasis on human decision-making capabilities, which can be further extended as a part of government competency.

Alhosani and Alhashmi (2024) underline that the successful implementation of AI in the public sector requires "contextualized, imaginative, and caring actions" (2024, p. 8). Such characterization is further expanded by conceptualizing five major success factors necessary for the positive adoption of AI in government services. They include: activation of local network trust, lowering financial barriers, riding the technological wave, focusing on tangible benefits, and staying engaged and showing commitment (Alhosani and Alhashmi, 2024). These factors may be perceived as actions aimed at building trust between the public and the developers of AI technology. When it comes to its implementation in the public sector, the government would occupy the position of the main author of the project although it may delegate the development of AI-driven tools to a third-party company. Even so, the government still would be the one in need of convincing the public of the necessity or benefit to deploy AI in the given public service area by utilizing the established levels of public trust in the government and raising them if necessary and possible.

2.5. Conceptualizing trust in AI

Trust in AI is generally conceptualized along two dimensions: human-like trust and a functionality trust (Glikson and Woolley, 2020; Choung et al., 2023; Thiebes et al. 2020):

- Human-like trust relates to users' perceptions of AI's benevolence, integrity, honesty, and fairness. It is fostered when AI looks, sounds, or behaves in human-like ways, i.e. engages in emotionally attuned interactions.

- Functionality trust concerns the technical competence, reliability, and safety of the AI technology. Increased when AI's performance is reliable and it operates in a transparent, understandable manner.

Alongside these factors, people's trust in AI also depends on the type of task it performs: for instance, trust tends to increase for technical or analytical tasks (e.g. data sorting and processing) and decrease for tasks where human judgement is valued (e.g. hiring people for jobs or criminal sentencing) (Glikson and Woolley, 2020). Moreover, scholars note that repeated experience with AI allows people to adjust their trust over time, which highlights the vulnerability of such trust in AI to performance failures of the technology itself.

2.6. Limitations of the existing literature

As mentioned in the introduction to this literature review chapter, contemporary scholarship on the effect of institutional factors on the support for AI in the public sector can be described as rather limited. While existing studies provide valuable insights into the technical capabilities of AI and individual-level perceptions of algorithmic systems, they tend to prioritize user-technology interaction while overlooking the broader institutional context in which such technologies are deployed. This creates a gap in the literature, particularly in the context of public sector AI, where the government acts not merely as a facilitator of technology, but as a central agent responsible for its implementation, regulation, and legitimacy.

This limitation can be partially explained by the fact that the adoption of AI in the public sector has been more slower and fragmented than in the private sector (Charles et al., 2022; DeSousa et al., 2020; Zuiderwijk et al., 2021). As a result, empirical research on the topic remains relatively scarce and context-dependent. Additionally, there has been inconsistency in findings on people's perceptions of algorithmic decision-making in general.

While some scholars have found that people prefer algorithmic decision-making over human decision making, others identified opposite patterns in their results (Haesevoets et al., 2024). A third category of studies revealed no significant differences in people's attitudes toward algorithmic or human decision-making (Otting and Maier, 2018; Prahla and Van Swol, 2017). These inconsistencies indicate the public attitudes toward AI are not stable, but conditional upon contextual factors that are not yet fully theorized.

Another important limitation lies in the conceptualization and measurement of trust itself. Although scholars have made significant progress in distinguishing types of trust in AI, such dimensions have been examined predominantly in isolation from trust in the institutions that use these technologies. The given separation brings up the risk of oversimplifying the process through which citizens form attitudes toward AI in governance. In saying that, the analysis doesn't take into consideration that evaluation of AI systems are shaped by pre-existing perceptions of trust in government. All together, the outlined limitations point to the need for a more integrated framework that connects individual-level perceptions of AI with macro-level institutional dynamics. Addressing this gap, the present study examines how trust in government influences public support for AI in the public sector, thus contributing to a more comprehensive understanding of the social acceptance of algorithm-driven governance.

2.7. Conclusion

This chapter has examined the existing literature on the use of AI in the public sector and factors shaping people's attitudes regarding its adoption. The carried out analysis demonstrated that AI is increasingly embedded in administrative processes, service delivery, and decision making, offering significant potential benefits in terms of efficiency, responsiveness, and evidence-based governance. At the same time, the literature highlights ethical, political, and social risks associated with algorithm-driven systems, particularly in

relation to bias, transparency, accountability, and the redistribution of decision making authority.

The key insight from this review is the pivotal role of trust in shaping public support for AI. Existing research shows that individuals evaluate AI systems not only based on their technical performance, but also through perceptions of reliability, fairness, and human-likeness. However, the discussion also highlights that trust in AI is inherently context-dependent and closely linked to the broader institutional environment in which these technologies are used.

Despite the growing body of scholarship on the topic, important gaps remain. Notably, the literature hasn't sufficiently integrated trust in government into the analysis of AI acceptance and it has not fully accounted for the contextual variability of public attitudes across different political and institutional settings.

With that in mind, the following chapter develops a theoretical framework that conceptualizes citizen support for AI in the public sector as a function of both trust in AI and trust in government. By linking the two, the study aims to provide a more comprehensive understanding of how people evaluate AI-driven governance.

Chapter 3: Theoretical Framework

3.1. Introduction

The previous chapter discussed the existing literature on the use of AI in the public sector. Particular attention has been paid to the factors that shape public acceptance of such technologies. A central insight from the literature is that trust plays an important role in shaping citizens' willingness to support and rely on AI-driven systems. Scholars in the field predominantly conceptualize trust at the level of the technology itself, focusing on the perceptions of technology's reliability, transparency, and human-like qualities. While such analysis provides an understanding of the topic pertinent to this study, there is a need to focus on the institutional context in which AI systems are developed and deployed.

This study emphasizes that AI can not be solely understood as an autonomous technology in the context of it being applied in the public sector. It may be seen as an extension of the government itself. Thus, public evaluations of AI in such regard are likely to be shaped by not only perception of it as a technology, but also as a part of the broader assessment of government institutions. With such an understanding in mind, trust in government can act as a prism through which people evaluate the risks and benefits associated with the use of AI in public services.

The given study utilizes a multidimensional conceptualization of trust in government, focusing on competence and benevolence as its core dimensions. The choice of applying a multidimensional approach is motivated by the inherently competitive nature of trust, which doesn't allow for the term to be reduced to a unified definition. Regarding trust in government, individuals may hold varying interpretations of what it means to trust the government. Therefore, it is essential to clarify the specific dimensions of trust, especially in the context of survey-based data collection of this study. Defining what is meant by trust in government enables appropriate operationalization and valid measurement.

This chapter has been structured to outline the theoretical framework that links trust in government to people's support for AI in the public sector. It begins by establishing the connection between trust in government and support for AI in public services, underlining that public attitudes toward such technologies are shaped by broader evaluations of government. Next, the chapter unfolds by defining the concept of trust and its relevant dimensions, which have been earlier developed by researchers in the field. The mentioned dimensions are justified as analytically and conceptually distinct, although complimentary components through which citizens evaluate governing institutions. Building on this foundation, there is an examination of how competence and benevolence influence support for AI in the public sector and interact between each other. The discussion of the above-mentioned relationships paves a way for the development of a set of hypotheses, the testing of which is discussed in the following chapters.

3.2. The role of trust in government in shaping support for AI in the public sector

Existing scholarship highlights social embeddedness as a defining characteristic of AI applications in the public sector, underlining the extent to which such technologies are intertwined with existing political and institutional structures. From this perspective, trust in AI as a technology alone is insufficient to explain citizens' willingness to engage with algorithm-driven systems. To account for the broader institutional dynamics, this thesis conceptualizes trust in government as a central variable necessary for understanding people's decision to trust or distrust AI systems in the public service sector. From a political science standpoint, incorporating trust in government can be seen as essential for developing a more comprehensive and theoretically grounded understanding of public attitudes towards AI use in the public sector.

Building on the role of institutional dynamics in shaping trust in AI, it is important to note that the use of AI in public services is closely associated with the risks of socio-political nature, which go beyond purely technical concerns. Public discussions surrounding AI in this context are often accompanied by openly expressed fears that algorithm-driven technologies may exacerbate surveillance of citizens and facilitate forms of control and suppression (Valle-Cruz, Garcia-Contreras and Gil-Garcia, 2024). Moreover, the increasing automation of tasks through AI has generated widespread concerns about the potential job losses and the replacement of human labor (Chen and Wen, 2021). These concerns signify how trust in AI being used in the public sector is inherently linked to people's evaluations of governmental conduct and authority, which constitute core components of trust in government.

3.3. Trust in government as a multidimensional concept

When discussing the trust in government, it is vital to differentiate between the types of trust as the concept itself can capture different dimensions of citizens' relationships with political institutions. Scholars conceptualize the trust in government as two-fold: generalized trust (directed toward institutions and the broader political system) and particularized trust (focused on individual public officials) (Houston and Harding, 2013). Additionally, trust in government may be domain-specific as people might express varying levels of trust in government across different policy areas (Lubell, 2007; Hardin, 2002). Nonetheless, as Devine et al. (2024) note, individuals can still hold a general sense of trust toward a particular political object, which constitutes an average of their trust across relevant domains. For the purposes of this study, the emphasis is placed on the general political trust, because the deployment of AI in the public sector is typically framed as an element of broader systemic reform and modernization, rather than the initiative of specific bureaucrats (Henman, 2020).

A domain-specific approach to trust in government, while being theoretically valid, would require a more in-depth analysis of the matter and currently exceeds the scope of this study.

Noting the above-mentioned, it is necessary to clarify the type and level of AI involvement addressed in this thesis, as varying degrees of authority delegated to AI systems in governance may generate different implications for people's trust in the technology. Although the use of AI in the public sector has become widespread, existing research suggests that governments tend to adopt a cautious approach when integrating the new technologies into administrative processes. One of the reasons for such caution may be the extensive data requirements associated with AI, deployment of which involves processing large volumes of sensitive personal information (Valle-Cruz et al., 2019). Considering the nature of the data, any technological shortcomings or misuse can be particularly costly, because they can significantly undermine public trust in both the technology and the government using it.

The nature of data related risks varies depending on the role assigned to AI in the public sector. When algorithm-driven technologies are used as decision-making tools, technical errors may result in inaccurate, unfair, or discriminatory outcomes (Heinrichs, 2022). In another way, when AI is integrated for primarily analytical and advisory purposes, flaws in the data processing might lead to incorrect assumptions and recommendations (Afroogh, 2024). In the case of Kazakhstan both types of risks are relevant as the country's government has actively introduced AI across various sectors of government. However, algorithm-driven technologies have not been granted (and aren't planned to be granted) full decision-making authority and are instead used as an assistance tool, which supports human judgement. Keeping that in mind, this thesis focuses on AI being used as an assistive technology in public services delivery.

Scholars widely recognize trust in government as a basis for effective governance and legitimacy. It reflects the citizens' willingness to accept vulnerability to governmental

authority based on the positive expectations of its competence, benevolence, and integrity (Grimmelikhuijsen and Knies, 2017; Devine et al., 2024). In such a context, trust is perceived as going beyond mere confidence in policy outcomes, because it signifies the citizens' moral and cognitive evaluations of whether government institutions are capable, fair, and act in the public's best interest. Moreover, trust in government can be multidimensional: for instance, deep-rooted trust is shaped by long-standing attitudes, moral evaluations, and institutional legitimacy (Grimmelikhuijsen, 2012). Consequently, trust in government should be understood as a relational and perceptual construct, associated with being a comprehensive notion that can be also analyzed through distinct dimensions.

Further empirical evidence also supports the idea that public trust in government functions as a critical antecedent that informs people's evaluation of certain governmental projects, including those that incorporate AI technologies (Kleizen et al., 2023). For instance, Kostka et al. (2023) identified a positive relationship between citizens' trust in government and their acceptance of facial recognition applications, suggesting that institutional credibility enhances perceived legitimacy of AI use in governance. Kleizen et al. (2023) found that the pre-existing general trustworthiness of government has a strong and significant effect on people's willingness to share personal data for government's AI-driven public service applications. Such findings indicate that citizens' willingness to engage with (or consent to) AI technologies in the public sector is deeply intertwined with their trust in government.

The three-dimensional approach to conceptualizing trust in government or a CBI model (competence, benevolence, and integrity) captures the above-mentioned complex nature of the term. It is based on an ABI model (ability, benevolence, and integrity) originally developed by Mayer et al. (1995) to explain how trust is formed in an organizational setting. Despite the wide adoption of an ABI model in various fields such as public administration, psychology, business administration, management, hospitality and tourism (Frazier et al.,

2017; Schnackenberg and Tomlinson, 2016; Braun et al., 2013; Dunn and Schweitzer, 2005; etc.), it has not been as extensively used in the study of political trust (Devine et al., 2024; Grimmelikhuijsen and Knies, 2017; Lean et al., 2009; etc.). Taking the above mentioned into consideration, the present empirical study seeks to contribute to the existing literature by applying the dimensions of the CBI model in the assessment of trust in government.

Prior to outlining the components of the noted CBI model, it is important to define the following. Scholars in the field use the term “perceived” when referring to competence, benevolence, and integrity in order to emphasize the inherently subjective nature of trust judgements. Trust in government, therefore, is not based on direct evaluations of governmental performance or intentions, but rather on citizens’ perceptions and individual assessments of these qualities.

3.4. The effects of competence and benevolence on support for AI in public sector

While all three dimensions of trust in government contribute to capturing trust in government, this study focuses only on two of them (perceived competence and perceived benevolence) as the most relevant for measuring trust in government in the context of AI implementation in the public sector in Kazakhstan. Competence is particularly relevant in the context of AI-driven public services as such systems are often perceived as unclear and difficult for the general public to understand, thus citizens may rely on existing perceptions of government competence as a basis for forming attitudes towards algorithm-driven technologies deployed in the public sector. Benevolence in such a context of low explainability becomes especially salient as it may signal the extent to which authorities can be expected to act in the interest of the public, even if their actions are not fully clear (Glickson and Woolley, 2020).

The dimension of integrity is excluded from the present study due to the specific characteristics of Kazakhstan classified as a consolidated authoritarian regime (Freedom House, 2025). Within the mentioned CBI model perceived integrity refers to adherence to ethical standards such as honesty, openness, consistency, and fulfilment of commitments. Hence, in the existing literature integrity judgements depend on citizens' ability to assess whether the authorities act transparently and in a predictable manner over time (Devine et al., 2024; Grimmelikhuijsen and Knies, 2017; Grimmelikhuijsen, 2010).

A valid analysis of integrity therefore requires conditions in which transparency, open access to information, and accountability mechanisms are present or visible enough to be assessed by citizens. In an authoritarian political context such conditions are structurally limited due to the restricted media freedom, non-transparent decision-making processes, and absence of authentic mechanisms to hold the government accountable for their actions (Glasius, 2018). As a result, citizens' ability to form reliable opinions regarding the integrity is constrained, making this dimension methodologically problematic for both the measurement and experimental manipulation.

Existing research in the field supports such observation and shows that trust in government in authoritarian settings is related to perceived government performance with regards to economic governance and policymaking rather than formal procedures and their fairness (Prati, 2022; Kim, 2010; Mishler and Rose, 2001). Moreover, scholars underline the presence of systemic self-censorship and preference falsification, which is characterized by citizens' modification of expressed attitudes towards authorities to align with regime expectations (Tannenbergh, 2022; Kuran, 1997). These factors suggest that manipulating perceived government integrity would be methodologically problematic as opposed to comparatively less politically sensitive dimensions of competence and benevolence.

From this perspective, perceived competence refers to citizens' assessments of the government's capacity to govern effectively. Scholars conceptualize competence as an evaluation of whether the governing institutions possess the necessary set of technical and administrative skills to perform their core functions and achieve intended policy outcomes (Devine et al., 2024; Grimmelikhuijsen and Knies, 2017; Grimmelikhuijsen, 2010). In the context of this study that focuses on citizens' attitudes towards the use of AI in the public sector, perceived **competence** reflects *people's evaluations of the government's technical expertise, administrative capacity, and professionalism in policy design and implementation, as well as decision-making.*

Perceived benevolence signifies the government's orientation towards citizens' welfare and public interest. The existing literature links this dimension of trust to evaluations of the motivations of governing organizations or intentions behind government action (Devine et al., 2024; Grimmelikhuijsen and Knies, 2017; Grimmelikhuijsen, 2010). Considering that previous research identified benevolence as a central determinant of trust judgements, this study follows the established scholarship and conceptualizes **benevolence** as *citizens' assessments of whether the government is genuinely motivated to act in the interest of the public.*

By using these dimensions to explain people's trust in government, scholars succeed in offering a valuable framework for examining the topic of this thesis, i.e. seeking to explain how trust in AI technology translates into institutional trust. In particular, competence and benevolence based framework allows to establish an understanding that trust in government doesn't solely depend on AI's technological performance, but is also concerned with additional relevant factors.

Inquiring on the relationship between the mentioned dimensions of trust - perceived competence and benevolence - contemporary research demonstrates that each different

dimension exerts a distinct effect on people's acceptance of policies and projects. Importantly, the mentioned trust dimensions are not treated uniformly across the existing literature. In particular, some scholars do not distinguish clearly between integrity and benevolence, but instead incorporate benevolence within the broader integrity judgements (Betzler et al., 2025; Kitt et al., 2021; Liu et al., 2020; Terwel et al., 2009). Hence, empirical findings regarding the relationship between these dimensions are not entirely consistent with each other and might offer different results. Additionally, with trust being recognized as domain-specific, the nature of given policies or projects might influence which dimension is more influential and how they interact with each other.

Building on the earlier discussed literature on trust in government and trust in AI, perceived competence is expected to play a central role in shaping citizens' support for AI in the public sector. As noted before, given the technical complexity and limited explainability of AI systems, people are often unable to directly evaluate the quality, reliability, or risks associated with AI. Under such conditions, perceived competency may serve as an important heuristic through which citizens assess whether the government that is designing, implementing, and overseeing AI in the public sector possesses the technical and administrative expertise. This expectation is consistent with contemporary empirical evidence. For example, Kitt et al. (2021) identify perceived competence as the most consistent and strongest driver of support for climate policy, suggesting that competence-based evaluations are especially influential when citizens face complex policy domains. Extending this finding to AI in the public sector, when the government is perceived as competent, citizens are more likely to believe that AI systems will function effectively and be managed responsibly. In line with such logic, this study hypothesizes that **when people perceive the government as competent, they will support the use of AI in the public sector (H1).**

In addition to competence, benevolence is also expected to significantly shape citizens' support for AI in the public sector. With AI systems often operating in ways opaque and hardly understandable to large groups of citizens, people may rely more on assumptions about government's intentions rather than some technical characteristics. Benevolence-based trust reflects the perception that the government acts in the public interest, demonstrating concern for their welfare and deploying technologies with socially beneficial outcomes. Recent research underlines the importance of this particular dimension. Devine et al. (2024) find benevolence to be the strongest determinant of trust in government with competence and integrity having a secondary and equal effect. In domains characterized by uncertainty and informational opaqueness – such as AI in the public sector – perceived benevolence may be expected to play a salient role in shaping citizens' attitudes. On this basis, the following hypothesis is formed: **when people perceive the government as benevolent, they will support the use of AI in the public sector (H2).**

The present study also expects benevolence to condition competence on support for AI in the public sector in line with insights from recent literature in the field. Existing research suggests that trust dimensions do not operate independently and interact in shaping public evaluations. For instance, Liu et al. (2020) demonstrate that competence-based trust increased renewable energy projects acceptance when perceived integrity (defined as “the extent to which responsible agents are perceived to be honest and transparent about their activities, and are concerned with public interests”) levels were low. However, when integrity-based trust levels were high, increased competency didn't have a significant effect on renewable projects acceptability. Similarly, Devine et al. 's (2024) research shows that benevolence conditions competence, showing that the latter may be insufficient to generate trust when government is perceived as lacking benevolence.

Applied to acceptance of AI in the public sector, this implies that competence signals (such as technical expertise and administrative capacity) are unlikely to translate into public support in the absence of perceived benevolence. Citizens may interpret high competence without benevolent intent as potentially harmful or misaligned with interests of the general public. In contrast, when benevolence is high, competence can reinforce confidence in the government's ability to deploy AI appropriately. Hence, this study hypothesizes that **the positive effect of perceived competence on support for AI in the public sector is conditioned by benevolence: when people don't perceive the government as benevolent, the presence of perceived competence won't lead to support for AI (H3).**

3.5. Conclusion

The theoretical framework developed in this chapter establishes the understanding of how social embeddedness of AI technology in the public sector is the defining feature that links trust in government with public support of such systems. To capture the mentioned relationship, a multidimensional approach of conceptualizing government trust has been adopted, particularly focusing on the notions of competence and benevolence. Competence in the given study reflects people's perceptions of government's technical expertise, administrative capacity, and professionalism to implement and design policies, as well as engage in decision-making. Benevolence is defined as public evaluation of the government's intentions to act in the interest of citizens.

Existing research in the field has demonstrated that both competence and benevolence may influence support for government policies and projects, including algorithm-driven technologies. Yet the two dimensions were also found to not be operating totally independent of each other. Instead, benevolence is believed to be conditioning competence in such a way, that competence alone might not be enough to drive people's support for AI in the public

sector in the absence of benevolence. The theoretical expectations derived from this chapter were framed into three separate hypotheses, which were empirically tested as a part of this thesis. The following chapters discuss the research design, methodology and results of the experimental data collection briefly mentioned in the earlier chapters.

Chapter 4: Research Design and Methodology

4.1. Introduction

As stated earlier, this thesis is aimed at examining the following research question: what effect do perceptions of governmental competence and benevolence have on citizens' support for AI in public services? The concepts of competence and benevolence have been selected as core components that signify the dimensions of trust in government. The two serve as independent variables in this study and have been precisely conceptualized in the previous chapter. The dependent variable of this research - as derived from the research question - is people's support for AI technology implemented in the public sector.

In order to identify the causal effect of independent variables on the dependent variable, as well as determining the nature of relationship between independent variables with regards to the dependent variable, this study employs a survey experiment. Such approach is especially appropriate for the selected topic as it allows for the controlled manipulation of informational cues related to government competence and benevolence while holding other factors constant. The random assignment of respondents to the treatment conditions enables the establishment of credible causal inference by isolating the independent effects of each dimension of trust on citizens' attitudes towards AI in the public sector. Notably, in comparison to observational approaches, the survey experiment also provides an opportunity to have a higher level of internal validity.

The survey was developed and carried out using the "Qualtrics" platform, which has been widely used by political science researchers and approved for student and faculty use by the Nazarbayev University. The key advantage of the platform for this study lies in the features, which enable experimental setups and randomization. Specifically, "Qualtrics" was used to embed vignettes, randomize the assignment of respondents to treatment groups, and standardize the presentation of survey questions to all participants.

The current chapter clearly outlines the research design and methodology of the study. It begins with an overview of the experimental method in political science, commonly used by researchers in the field to test theories. Next, there is a description of treatment groups and randomization procedure, which is followed by the discussion of pre-treatment measures, post-treatment measures, and outcome measures. Additionally, the chapter contains information about the estimation strategy used to assess treatment effects, as well as sample and data collection process. The chapter concludes with stating considerations regarding the validity of the study and adherence to ethical principles.

4.2. Experimental design overview

This study employs a two-by-two vignette-based survey experiment to assess how perceptions of governmental competence and benevolence shape citizen support for AI-driven assistance tools in public services. An experimental approach is selected because it enables credible causal inference through the observation of the effects of manipulated independent variables in a controlled environment (Druckman et al., 2011). The key advantage of experimental research in the context of this thesis lies in the ability to randomly assign treatments to respondents, thus identifying causal relationships rather than relying on observational correlations (Druckman et al., 2011). In other words, internal validity of experimental research in this context is especially valuable (Bhattacharjee, 2012). This is particularly important for testing the hypotheses and theoretical framework developed in the given study, which focuses on distinct dimensions of trust in government and their influence on the acceptance of AI.

It is necessary to emphasize that an observational study of different dimensions of trust in government would present the following limitations. Firstly, perceived competence and benevolence are often intertwined, which might make it difficult to distinguish which

dimension drives observed attitudes. Secondly, as mentioned previously, trust in government is accepted as a complex and domain-dependent notion shaped by policy types, previous experiences, and individual predispositions. In this regard, experimental manipulation allows for an isolation of the dimensions of trust and examination of whether they independently affect public acceptance of AI or condition each other.

Notably, experimental research has not been very common in contemporary scholarship examining trust in government. In addition to previously discussed studies by Liu et al. (2020), Devine et al. (2024), there is a limited body of work that employs experimental methods to measure and manipulate forms of political trust. Hence, it is vital to provide the context of the research that was carried out in the mentioned manner.

Among the few is Peyton (2020), that in a study of the relationship between trust in government and public demand for redistributive policies in the U.S. provides evidence of the possibility to influence the level of trust in government through provision of certain information (their study utilizes Opinion Pieces presented as written in “The New York Times” newspaper by a former federal government employee).

Campbell (2023) also utilized a vignette-based experiment to test the impact of public participation in the policymaking process on trust in government. By exposing the respondents to informational texts about the involvement of citizens in the policymaking and the success or failure of the proposed initiative, the researcher found the marginal effect of participatory policymaking on trust in government, as well as determining the critical importance of performance in the said relationship. While public participation in the policymaking process is not explicitly framed as a dimension of trust in government, the testing process can be perceived as an attempt to signal varying levels of competence and benevolence of the government.

Hansen (2023) applies a large-scale randomized survey experiment to manipulate warmth and friendliness of public employees in the decision-making process. The mentioned variables are used to examine their effect on trust in government institutions. Although Hansen's (2023) study does not directly match the theoretical direction of this thesis, it may be treated as an example of a similar manipulation strategy. Particularly, the warmth and friendliness of public employees attribute to dimensions of trust in government. Therefore, contemporary research is characterized by valid attempts at experimental manipulation of factors that contribute to the notion of trust in government.

The experimental design of this thesis is structured to manipulate informational frames related to two theoretically central to this study dimensions of trust in government: perceived competence and perceived benevolence. The design contrasts three positive treatments with a neutral baseline condition (i.e. control group) instead of using a symmetrical high-versus-low treatment structure. Respondents are randomly assigned to one of four groups: high competence treatment, high benevolence treatment, high competence and benevolence treatment, no treatment (receiving neutral, non-evaluative information). The following subchapters provide a more detail-oriented description of the testing process and data collection.

4.3. Treatment groups

The two-by-two vignette-based survey experiment that introduces three positive treatment conditions alongside a neutral baseline, i.e. a control group (Table 1). Both theoretical and methodological considerations explain this design choice. Individuals may hold strong negative predispositions toward governmental institutions, especially in political environments characterized by relatively low levels of institutional trust. Using overly

negative frames, such as low competence or low benevolence treatments, brings up the risk of creating floor effects that prevent evaluations that are already low from falling any lower.

Table 1: Treatment groups breakdown

Group A	High competence treatment
Group B	High benevolence treatment
Group C	High competence and benevolence treatment
Group D (control)	Neutral, non-evaluative information (no treatment)

Contemporary research on institutional trust levels in Kazakhstan shows mixed results. For instance, Makulbayeva et al. (2025) argue that institutional trust in Kazakhstan has been declining over the past decade and attribute this trend to political system performance problems, corruption perceptions, and limited political participation. At the same time, findings from the 2025 survey conducted by The Bureau for Express Monitoring of Public Opinion “Demoscope” indicate that 62,7% of citizens believe that the government is failing to solve pressing social and economic problems in the country (Demoscope, 2025). Moreover, 41.9% of respondents claim that in 2025 the standard of people’s living has dropped (Demoscope, 2025). Such findings suggest that public attitudes toward government in Kazakhstan might be polarized and heterogeneous. Considering this variation in levels of institutional trust, using strongly negative treatments will most definitely create floor effects among respondents with an already low level of trust in the government of Kazakhstan.

The first treatment condition (Table 2) is designed to manipulate perceptions of government competence. This vignette emphasizes the state’s administrative capacity, technical expertise, and effectiveness in implementing complex policies. The manipulation is achieved through repeated references to centralized coordination, digital infrastructure, and measurable performance outcomes. For instance, the text highlights the successful

implementation of national platforms, rapid processing times of citizens' requests, and high levels of procedural accuracy, supported by references to external audits. The statistics are used to reinforce an image of a capable and efficient government, without invoking motivations related to citizen welfare or moral intent. By doing so, the treatment isolates competence as a dimension of trust by signaling the government's ability to deliver effective policy outcomes.

Table 2: Vignette A - Competence level manipulation text for Group A

Over the past decade Kazakhstan's government has consistently demonstrated strong administrative and technical capacity in implementing complex reforms and managing large-scale public programs. Major national initiatives have been executed according to clearly defined strategic plans with centralized coordination across ministries and akimats (local administration).

Government institutions have successfully modernized infrastructure in multiple public service sectors, integrating digital and administrative systems to improve speed, accuracy, and coordination. In 2022 the centralized platform "e-Otinish" was launched to streamline communication between citizens and state institutions. The platform enables users to submit appeals, track case progress, file complaints, and initiate legal claims without visiting state institutions. By the end of 2025, more than 5 million appeals have been processed with the vast majority (90%) being responded to within minimal deadlines (few hours to 3 days).

Public service delivery has further been supported by centralized administrative platforms using automated verification systems and standardized processing protocols, resulting in rapid review times and exceptionally high levels of procedural accuracy, according to independent external audits conducted in 2025 by "Deloitte" and "PwC" firms.

Government agencies also demonstrated a high level of coordination in managing import and export processes, contributing to the efficient implementation of national trade objectives. Through structured interdepartmental communication, precise allocation of logistical resources, and timely execution of administrative procedures, agencies ensured consistent operational performance. As a result, total trade turnover reached \$150 billion in 2025, exceeding levels observed over the previous five years.

The second treatment condition (Table 3) manipulates perceptions of government benevolence. In contrast to the competence treatment, this vignette focuses on the intentions and citizen-oriented motivations of the state. The text emphasizes the prioritization of public well-being, social protection, and responsiveness to citizen needs. The manipulation is implemented through descriptions of public consultations, feedback mechanisms, and targeted

support for vulnerable populations. Additionally, the vignette highlights government actions during a national crisis, portraying authorities as attentive and supportive in times of need. The inclusion of survey-based evidence indicating that citizens perceive the government as caring further reinforces this framing. Overall, this condition isolates benevolence by presenting the government as empathetic, responsive, and motivated to act in the public interest, without emphasizing technical efficiency or performance capacity.

Table 3: Vignette B - Benevolence level manipulation text for Group B

Over the past decade, the government of Kazakhstan has consistently emphasized that public policy should prioritize well-being, dignity, and long-term security of its citizens. National development strategies have repeatedly highlighted social protection, equal access to opportunities, and support for vulnerable groups as central policy objectives.

To ensure that public opinion reaches state institutions, feedback mechanisms have been established across the country. Public forums and listening sessions have been held in both urban and rural areas, where citizens were able to openly share their concerns and community needs. As the result, the government adjusted public welfare programs and initiated new policies and projects, aimed at prioritizing the vulnerable social groups, as well as the population at large. A public opinion poll conducted by the “Pew Research Center” in 2025 found that 78% of respondents felt that “the government genuinely cares about the well-being of people like me” while 82% said they believed the government policies reflect citizens’ interests above all else.

Notably, the government demonstrated strong concern for citizens during the 2024 floods that affected the majority of regions in Kazakhstan. In addition to providing financial assistance and conducting rescue operations, the state established support hotlines offering psychological assistance to the affected citizens. Surveys conducted afterwards indicated that many citizens viewed these measures as evidence of the government’s commitment to protect the well-being of people during times of crisis.

The third treatment condition (Table 4) combines both competence and benevolence cues within a single narrative. This vignette integrates elements from the previous two treatments, presenting the government as both technically capable and socially responsive. The manipulation is achieved by simultaneously highlighting administrative efficiency, rapid policy implementation, and coordinated governance, alongside strong commitments to social welfare, poverty reduction, and citizen engagement. For example, the text links efficient

administrative processes to improved welfare outcomes, such as reduced poverty and timely delivery of financial assistance during crises. By merging these dimensions, the treatment allows for the assessment of whether combined signals of competence and benevolence produce an effect on attitudes toward the implementation of AI technologies in the public sector.

Table 4: Vignette C - Competence and benevolence level manipulation text for Group C

Over the past decade, the Government of Kazakhstan has demonstrated a consistently high level of administrative and technical capacity while maintaining a strong commitment to protecting citizens' well-being. Major reforms have been implemented according to clearly defined strategic plans, supported by coordinated efforts across ministries and akimats (local administration).

Government initiatives have expanded targeted assistance programs for low-income families, rural communities, and individuals facing economic hardship. Social support mechanisms have been strengthened to ensure that benefits reach those most in need, with regular public reporting aimed at increasing transparency and accountability. As the result, by the end of 2025 the amount of people living below the poverty line dropped from 5.1% to 1%.

During periods of crisis, authorities have publicly committed to protecting citizens from economic and social risks, introducing relief measures designed to reduce financial burdens on households and small businesses. For example, after the 2024 floods in several regions expedited procedures were launched to deliver financial assistance to the affected population without bureaucratic delays, allowing the people to collect funds within few days after the incident. Public consultations and feedback mechanisms have also been expanded to allow citizens to voice concerns. During and after the floods direct communication lines were established, through which people had an opportunity to resolve their issues within unprecedentedly short periods of time – from few hours to 3 days.

The fourth vignette is designed for a control group (Table 5). It does not include any manipulation related to government performance or intentions. Instead, respondents are presented with a neutral, fact-based description of the 2026 Winter Olympic Games. The content is deliberately unrelated to governance, public policy, or institutional evaluation, and avoids both performance-related and normative language. This condition establishes a baseline against which the effects of the other treatments can be compared, ensuring that any

observed differences in outcomes are attributed to the specific government trust-related manipulations.

Table 5: Vignette D - No manipulation text for Control Group

The Winter Olympic Games are a major international sporting event that brings together athletes from around the world to compete in a wide range of disciplines. The 2026 Winter Olympics were hosted by Milan and Alpine mountain resort town of Cortina d'Ampezzo in Italy, featuring competition across sports such as ice hockey, figure skating, biathlon, bobsleigh, alpine skiing, cross-country skiing, freestyle skiing, snowboarding, short track speed skating, curling, luge, Nordic combined, skeleton, ski mountaineering, ski jumping.

The 2026 Games brought together participants from 93 countries. Delegations from European, American, and Asian countries were the largest in terms of the participating athletes. Norway, USA, Netherlands, Italy, and Germany secured the highest number of medals. Brazil was the country closest to equator to win a medal.

The oldest medalist in the 2026 Olympic Games was a 46-year old Silvana Tirinzoni, a winner of the silver medal in women's curling from Switzerland. The youngest medalist was from the Republic of Korea – 17-year old Choi Gaon, who secured gold in the women's snowboarding halfpipe. Moreover, these Games were referred to as the most gender-balanced Winter Olympics in history with women making up 47% of all athletes.

In order to ensure unbiased estimation of treatment effects, respondents were randomly assigned to one of four experimental conditions using the built-in randomization feature of the “Qualtrics” platform. The randomization occurred automatically upon entering the survey, meaning that there was no influence from the main investigator or respondents themselves.

4.4. Pre-treatment measures

Pre-treatment measures refer to variables collected before the respondents are exposed to the experimental treatment (Bhattacharjee, 2012). These measures capture baseline characteristics and prior attitudes that might influence how respondents react to the manipulation and evaluate information presented in the survey. Including such measures allows to account for individual-level differences, which possibly affect the observed

treatment effects. In this study, the survey begins with a set of demographic questions that record respondents' age, gender, citizenship status, place of upbringing, academic program level, and field of study. These variables serve as control variables. Additionally, there is a measurement of respondents' level of interest in politics in general that may influence the extent to which individuals process political information presented in the questionnaire.

The survey also includes several attitudinal measures related to the core themes of the study. Firstly, respondents were asked to evaluate their overall level of trust in government on a ten-point Likert-type scale, providing a baseline measure of institutional trust prior to the experimental manipulation. Secondly, as the study focuses on the acceptance of AI in public services, respondents are asked to express the extent of their familiarity with AI and overall attitudes towards such algorithm-driven technologies. These variables capture prior exposure to and perceptions of AI that might independently shape the respondents' support for AI in public services.

4.5. Post-treatment measures and attention checks

To assess whether the experimental manipulation achieved the intended purpose, the survey includes a set of manipulation check questions asked after the treatment. Perceived government competence is captured through items measuring the government's effectiveness in dealing with national problems and its technical and administrative capacity to implement policies. Perceived benevolence is measured through items assessing the extent to which the government cares about citizens' well-being and acts in the public interest. All of these items use 10-point Likert-type scales, ensuring consistency in measurement across all responses. These variables allow for empirical verification that the competence and benevolence treatments successfully shifted respondents' perceptions in the expected directions.

The survey also includes attention check questions to ensure data quality and improve accuracy of the results. Each treatment is followed by one question regarding some information presented in the manipulation text. The attention check questions were formulated in a way to not come out as too general, while simultaneously being specific enough for the respondent to be able to answer with ease. For example, the high competence text was followed by the question about which global firms conducted audits of the mentioned administrative platforms.

4.6. Outcome measures

Every treatment is followed by a scenario that reflects Kazakhstan's policy environment, where the AI-powered video analytics system called “Sergek” is being used in public safety and traffic management domains. At first, the respondents are presented with information about prior experience of the government in using the system, underlining its ability to automatically identify traffic offenses and generate administrative reports. Next, the survey participants are informed of the government plans to expand the usage of “Sergek” by adding an advanced AI-backed facial recognition feature, which would “use AI algorithms to analyze live camera footage, match facial data against authorized databases, and flag individuals potentially involved in criminal offenses in public places”. The goal of such enhancement is stated as lowering crime rates and increasing the efficiency of the law enforcement in identifying suspects in crowded urban areas.

The text clarifies that AI technologies primarily serve as assistive tools supporting human decision-makers rather than autonomous decision-making systems. Such framing is consistent with Kazakhstan's current governmental strategies, which integrate algorithm-driven technologies to enhance professional judgment and administrative procedures rather than to replace human authority. Therefore, the presented scenario is more

plausible and respondents are expected to be more engaged with the treatment materials when the experiment is conducted in a realistic national context. The exact text of the presented scenario can be found on table 6 below.

Table 6: Scenario about the usage of AI in public services in Kazakhstan

In the recent years Kazakhstan has implemented digital monitoring technologies to improve public safety and traffic management. One example is the “Sergek” system, which has been deployed in major cities to monitor road traffic and detect violations such as speeding or running red lights. The system relies on AI-powered video analytics to automatically identify traffic offenses and generate administrative reports, supporting more systematic enforcement on the roads.

Building on this experience, the government is now planning to expand the system by introducing an advanced AI-backed facial recognition feature. The upgraded system would use AI algorithms to analyze live camera footage, match facial data against authorized databases, and flag individuals potentially involved in criminal offenses in public places. The purpose of the AI enhancement is to lower crime rates and assist law enforcement in identifying suspects more efficiently in crowded urban environments.

Authorities emphasize that the AI system will function strictly as a decision-support tool. While the technology may detect patterns, generate alerts, and suggest potential matches, final decisions (including identity verification, investigation, and any legal action) will remain under the authority of human officers. The proposed expansion is presented as an AI-driven technological upgrade designed to strengthen public security while preserving human oversight in enforcement processes.

The AI-related scenario is also followed by an attention check question, which asks the respondents to identify which road traffic monitoring system has been deployed in Kazakhstan.

The primary outcome variables (measured after the respondents read the scenario) relate to support for and comfort with AI in public service delivery, specifically in the context of AI-enhanced surveillance through the “Sergek” system. In particular, support for the implementation of the AI-driven public security system is measured using a 10-point Likert-type scale, ranging from “strongly oppose” (1) to “strongly support” (10). This item captures respondents’ policy-level approval of AI adoption in law enforcement. A second key outcome variable - comfort with the system operating in public spaces - is measured on a

similar 10-point Likert-type scale, ranging from “very uncomfortable” (1) to “very comfortable” (10). While the first measure reflects normative support, the second captures affective acceptance, allowing for a more nuanced assessment of public attitudes toward AI technologies.

4.7. Estimation strategy

The following regression model is used to estimate the causal effect of the experimental treatments on dependent variable:

$$Y_i = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + e_i$$

where Y_i stands for the level of support for AI in public services for respondent i . The variables X_1 and X_2 are binary indicators that capture exposure to the high competence and high benevolence treatments (the value of 1 is taken if the respondent is assigned to the corresponding treatment and 0 is if not). The interaction term $X_1 X_2$ indicates joint exposure to both treatments. The intercept term α represents the level of support for AI in public services among the respondents in the control group (those, who were not exposed to any treatment). The coefficient β_1 estimates the effect of the competence treatment relative to the control condition when benevolence is absent and β_2 indicates the effect of the benevolence treatment relative to the control condition when competence is absent. The interaction term β_3 signifies whether and how the effect of competence changes in the presence of benevolence, thus allowing to estimate the conditional treatment effect.

The presented approach allows for all hypotheses to be tested within a single framework (Table 7). Despite being captured in a single main regression model, in practice the effects of independent variables are estimated in two versions. Firstly, a baseline model is estimated without additional controls and relies only on randomized assignment of treatments. Secondly, a full model includes pre-treatment variables to improve the precision of estimates.

Both versions are estimated using ordinary least squares (OLS) regression with robust standard errors.

To clarify further, this estimation strategy is primarily aimed at identifying the average treatment effect (ATE) of perceived competence and benevolence dimensions on support for AI in public services. In the selected model, given the randomized assignment of respondents to treatment conditions, the coefficients on the treatment indicators can be interpreted as ATEs. The coefficient β_1 represents the difference in average support for AI in public services between respondents exposed to the high competence treatment and in the control group when competence is not present. In the same manner, β_2 represents the difference in mean outcomes between respondents that are exposed to the high benevolence treatment and the control group when benevolence is missing. The same logic applies to β_3 as it reflects how the effect of competence changes in the presence of benevolence.

Table 7: Hypotheses and their corresponding model coefficients

Hypothesis	Coefficient	Expected direction of the estimate
Hypothesis 1: When people perceive the government as competent, they will support the use of AI in the public sector	β_1	$\beta_1 > 0$
Hypothesis 2: When people perceive the government as benevolent, they will support the use of AI in the public sector	β_2	$\beta_2 > 0$
Hypothesis 3: The positive effect of perceived competence on support for AI in the public sector is conditioned by benevolence: when people don't perceive the government as benevolent, the presence of perceived competence won't lead to support for AI	β_3	$\beta_3 > 0$

Note: $E[Y]$ represents the expected value or, in other words, the average value of the outcome variable

The dependent variable - support for AI in the public sector - is treated as a continuous variable. The independent variables correspond with the applied experimental treatments and are coded as binary: the value of 1 is taken if the respondent has been exposed to the high competence or high benevolence treatment and the value of 0 is taken if the treatment wasn't given. The interaction term is the product of the two indicators and captures joint exposure to high competence and benevolence.

4.8. Validity

As previously mentioned, the experimental design of this study was selected to increase the internal validity. The core component lies in the assignment of randomization, which eliminates selection bias by ensuring that designated treatment groups are not correlated with pre-existing traits of respondents. Moreover, the vignette-based two-by-two survey design contains controlled treatment manipulation aimed at influencing only the intended variables. Additionally, the given design choice incorporates a control group with a neutral baseline condition.

The main threat to the internal validity of this study would be posed by the weakness of manipulation. In saying that, high competence and benevolence treatments might not actually increase the level of such dimensions of trust in government. Manipulation checks are included in the questionnaire to identify whether the manipulation has provided some outcomes. Nonetheless, the mentioned aspect of experimental design should be treated as a potential limitation of the study.

Regarding external validity of the study, a few limitations should be taken into consideration. Firstly, the student sample might be insufficient to establish the causal relationship if the effect of competence and benevolence manipulation depends on the baseline level of trust. Secondly, the problem arises if the sample presents minimal variation

in the mentioned dimensions of trust in government variables. To mitigate such threats, manipulation check questions, as well as measurements of pre-existing levels of trust in government have been included in the survey.

4.9. Sample and data collection

This study uses a sample of 210 university students drawn from those studying in Nazarbayev University in Astana, Kazakhstan. Respondents were recruited through an email invitation in three languages (English, Kazakh, and Russian) distributed via university mailing system (Table A1, Appendix A). Participation was voluntary, anonymous, and respondents could complete the questionnaire on any devices and at any time convenient for them.

In order to ensure accessibility and inclusiveness, the survey itself was created in three languages - English, Kazakh, and Russian. Respondents selected their preferred language by accessing the survey through a corresponding language specific link. Once a language was selected, participants were required to complete the survey in that language and couldn't switch between versions during participation. This design choice was carried out to minimize potential variation in interpretation of presented information based on language preferences.

The usage of a student sample allows for the establishment of a controlled setting for conducting a survey experiment. Although a representative sample of the whole population would be considered the exemplary standard for an empirical analysis, student samples have been actively used in the field of social sciences to conduct research. For instance, Druckman and Kam (2009) found student subjects to not be intrinsically posing a threat to experimental study's external validity. That is not to say that the nature of such samples does not matter. The considerations for the problematic feature of student samples is especially relevant when the goal of the study is population-level generalization. In the given study, however, the

emphasis is made on testing the developed theory-based hypotheses and identifying the presence of causal mechanisms. More detailed discussion of validity concerns can be found in the following subchapters.

4.10. Ethical considerations

The study was formulated to ensure the adherence to ethical standards for research involving human subjects. Prior to participation all respondents were presented with an informed consent form at the beginning of the survey. The consent form was displayed immediately upon accessing the survey link and before any questions were asked. Participants were required to check the respective box “I agree” in order to proceed to the questionnaire. The participants who selected “I disagree” were not shown any questions and received an “End of Survey” message.

Before conducting the survey and collecting data, the survey and research protocol was approved by the Nazarbayev University School of Sciences and Humanities Institutional Research Ethics Committee.

Important to clarify, that the survey didn’t include any sensitive or potentially harmful questions. All responses were collected anonymously and no personal identifiable information was collected. The “Qualtrics” platform through which the survey was administered ensured anonymity and confidentiality in the process of data collection. Participation in the study was entirely voluntary and respondents were able to stop their participation at any time by exiting the survey. Hence, the risk to participants has been assessed as less than minimal.

4.11. Conclusion

This chapter presented a detailed overview of the research design and methodology selected to test the hypotheses developed earlier in the thesis. A controlled survey

experimental design was chosen to identify how perceptions of government competence and benevolence shape the citizen support for AI in public services. Such an approach gives an opportunity to assess the causal relationship between the independent and dependent variables, i.e. to directly test whether the expectations derived from the theoretical framework are supported.

The selected estimation strategy is characterized as a basic linear regression model and which matches the two-by-two vignette-based experimental survey design. It allows for an estimation of average treatment effects and captures the interaction between the two independent variables, which correspond with the all three hypotheses of the thesis.

The chapter also addressed potential limitations of the study related to the use of a student sample. While this sample isn't fully representative of the broader population, it is appropriate for the primary objective of this thesis, which is to test the developed theory by applying scientific research method skills. Furthermore, the emphasis of this study is placed on identifying causal relationships rather than coming up with generalizable claims about the whole population.

Overall, the experimental design and estimation strategy of this study was developed to ensure that the assessment is methodologically precise and careful. With that in mind, the following chapter presents the empirical findings and discussion of whether the results support the proposed hypotheses.

Chapter 5: Findings

5.1. Introduction

This chapter presents the empirical findings of the given study. The reporting of the results is done in several steps. Firstly, this chapter discusses the descriptive statistics and sample characteristics to contextualize the available data. Secondly, comparisons across treatment groups are realized to get an initial overview of differences in support for AI in the public sector. Thirdly, the regression models are analyzed to test the three hypotheses. Together these steps are aimed to identify the independent and conditional effects of competence and benevolence, while accounting for relevant individual characteristics of the sample.

5.2. Sample characteristics

The full sample consists of 210 respondents. As shown in Table 11 the majority of the students are aged 18-24 (60%) followed by 25-34 (29.5%). Gender distribution is balanced with 53.3% of female respondents and 46.2% male respondents (0.5% preferred not to disclose their gender). This reduces concerns regarding gender-driven bias in attitudes toward AI, although such variable was still treated as a control in the regression models.

Majority of the respondents are residents of Kazakhstan (88.1%) and of an urban upbringing (87.1%). The sample is relatively evenly distributed between STEM (47.6%) and non-STEM (49.1%) fields of study. Moreover, there are more Master's level students among the respondents (40.9%), which are followed by the Bachelor's (38.6%), Doctoral (20%) and Foundation Year (0.5%) students.

Table 8: Sample characteristics

Variable	Categories	Frequency (N)	%
Age	18-24	126	60.0
	25-34	62	29.5
	35-44	21	10.0
	45-54	1	0.5
Gender	Male	97	46.2
	Female	112	53.3
	Prefer not to say	1	0.5
Residency	Non-resident	25	11.9
	Resident	185	88.1
Upbringing	Rural	27	12.9
	Urban	183	87.1
Academic Program	Foundation Year	1	0.5
	Bachelor's	81	38.6
	Master's	86	40.9
	Doctoral	42	20.0
Field of study	Non-STEM	103	49.1
	STEM	100	47.6
	Not sure	7	3.3

Overall, the sample is characterized as young, educated, urban, and digitally exposed. This will be taken into account when interpreting the results in the following chapter.

In order to provide a more precise assessment of the experimental results, the analysis is conducted across two samples: the full sample ($N = 210$) and a filtered sample of respondents who passed the post-treatment attention check questions in the survey ($N = 163$). This separation enables evaluation of whether the estimated treatment effects are sensitive to respondents' engagement with the experimental stimulants. While the full sample is characterized as the primary basis for inference, the attention-filtered sample serves as a robustness check.

With that in mind, the following subchapters are organized into two parallel subsections. Each subsection presents an analysis for one of the samples, full and filtered. In

particular, descriptive statistics are reported by relevant variables to provide an overview of sample composition. Next, difference-in-means tests are used to estimate the ATE across experimental conditions. Moreover, regression analyses are shown to account for covariates and test the robustness of the estimated effects under alternative model specifications.

5.3. Average treatments effects in the full sample

5.3.1. Descriptive Statistics

The descriptive statistics provide the respondents' baseline attitudes towards politics, government, and AI, as well as distribution of key variables used in the analysis (Table B1, Appendix B). They show that among all participants there is a moderate level of interest in politics with a mean of the variable being equal to 6.34. Baseline trust in government is comparatively lower with a mean of 4.29, which indicates initial skepticism of the sample toward governmental institutions. Such distribution indicates that the selection of a research design as contrasting three positive treatments with a neutral baseline condition was the correct choice as respondents did not enter the experiment with uniformly high trust in government.

Respondents also demonstrated increased familiarity with AI technologies (mean = 7.27) and moderately positive general attitudes toward AI (mean = 7.27). Hence, the sample is found to be not only aware of AI, but also predisposed to evaluate it more favorably. Additionally, the post-treatment measures of perceived competence (mean = 5.06) and perceived benevolence (mean = 4.62) are both around the midpoint of a Likert scale. The benevolence has been evaluated more negatively. The dispersion in both variables is moderate, which highlights the sufficiency of variation for identifying treatment effects.

The primary outcome variable (support for AI in the public sector) has a mean of 5.90 with a median of 6.5. This reflects a moderately positive but not overwhelming level of

support, suggesting that respondents are on average cautious in supporting AI in public services. The relatively large standard deviation (2.52) suggests considerable heterogeneity in attitudes towards AI in the public sector, which is essential for detecting the influence of experimental manipulations.

5.3.2. Randomization and manipulation check

In order to assess the effectiveness of random assignment, baseline characteristics were compared across four experimental groups: group A (high competence), group B (high benevolence), group C (high competence and benevolence), and group D (control) (Table B3, Appendix B). The comparison includes both attitudinal variables and demographic characteristics.

Across the attitudinal measures, group means appear rather similar. Interest in politics ranges from 6.00 (SD = 2.67) in group A to 6.94 (SD = 2.38) in group C. Trust in government varies between 4.02 (SD = 1.95) in group B and 4.80 (SD = 1.86) in group C. Familiarity with AI is relatively consistent across groups with means between 7.08 (SD = 1.55) and 7.41 (1.75). Attitudes toward AI show somewhat greater variation with the lowest mean in the control group D (5.77, SD = 2.37) and the highest in group B (6.94, SD = 2.35).

The distribution of gender is comparable across conditions with female respondents taking up between 45.3% and 57.4%, while male respondents comprised between 42 and 54.7%. Age distribution is concentrated in the 18-24 and 25-34 categories across all groups.

In terms of field of study, both STEM and non-STEM backgrounds are represented in each group. The share of STEM respondents ranges from 37% (group C) to 54.7% (group D), while non-STEM respondents range from 41.5% (group D) to 59.3% (group C). A small proportion of respondents reported being unsure. Regarding the level of academic program, the majority of respondents reported being enrolled in Bachelor's and Master's programs

across all groups. Bachelor's students take up the range from 35.2% (group C) to 44% (group B). Master's students constitute between 37% (group C) and 49.1% (group A), while doctoral students range from 13.2% (group A) to 27.8% (group C). Most respondents are from an urban upbringing, ranging from 83% (group D) to 94% (group B) with rural background accounting for a smaller share. Similarly, the majority of participants are residents of Kazakhstan with proportions between 84% (group B) and 90.6% (group A).

The descriptive statistics for manipulation check questions across four experimental groups suggest that the treatments did in fact shift the respondents' perceptions of governmental competence and benevolence in the intended direction. For instance, respondents in group C reported the highest average levels of perceived competence with a mean of 5.39 (SD = 1.88) and perceived benevolence with a mean of 4.95 (SD = 2.12). Additionally, those in groups A and B expressed higher perceptions of perceived competence and benevolence than those in the control group D (Table B5, Appendix B).

The sample sizes across groups are comparable: 53 respondents in group A, 50 in group B, 54 in group C, and 53 in group D.

5.3.3. Difference-in-means test

The comparison of mean levels of support for AI across the experimental groups was carried out to examine the variation in the outcome across treatment conditions and relative to the control group. The control group has an average support level of 5.77 on the 10-point Likert scale, which depicts a relatively positive baseline attitude toward the use of AI in the public sector. Against this finding, the treatment conditions reveal different patterns.

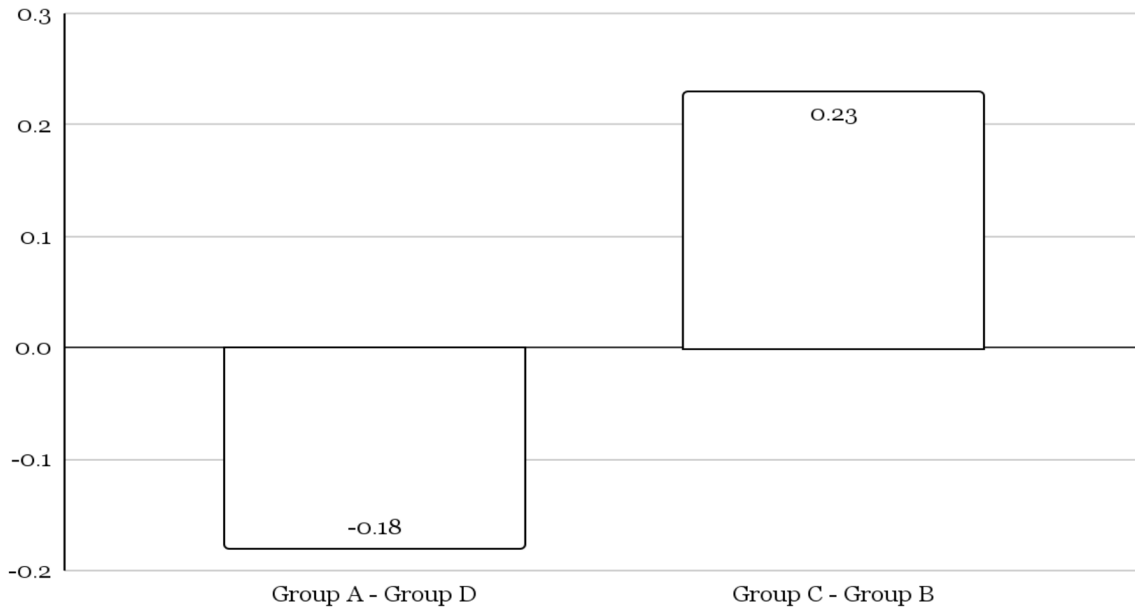
For instance, the high competence treatment is associated with a slight decrease in support (mean = 5.59) that corresponds to a difference of 0.18 compared to the control group. This suggests that emphasizing government's effectiveness and technical capacity alone is not

sufficient to drive support for AI. Contrasting to that, high benevolence treatment is characterized by a higher average level of support (mean = 6.00) with an increase of 0.23 with regards to the control group. Hence, framing the government as acting in public interest and prioritizing citizen well-being seems more effective in fostering positive attitudes towards AI in the public sector.

The combined high competence and benevolence treatment produces the highest level of support among all groups (mean = 6.23) with a difference of 0.45 compared to the control group. Such a pattern indicates a potential reinforcing effect of both dimensions of trust when presented together. Notably, however, the observed differences of all groups are not statistically significant, therefore further regression analysis is necessary to carry out precise estimation of treatment effects and their interaction (Table B7, Appendix B).

Figure 1 presents a pairwise comparison between treatment groups. Particularly, it depicts the contrast between the high competence treatment group (A) and the control group (D), as well as the comparison between the combined treatment group (C) and the high benevolence treatment group (B). The bar plot specifically corresponds to the third hypothesis, which states that the positive effect of perceived competence on support for AI in the public sector is conditioned by benevolence.

Figure 1: Treatment group means differences (full sample)



5.3.4. Regression results

A series of regression models was run to assess the effect of experimental treatments on support for AI in the public services. The models separately incorporate interaction terms and control variables to test the hypotheses and perform robustness checks of the observed relationship (Table 9).

Model 1 estimates the effect of treatment conditions without the additional controls. The coefficient for the competence treatment is negative and is not statistically significant, thus it does not support H1, which is associated with an understanding that exposure to information emphasizing competence of the government independently increases support for AI in the public sector. The benevolence treatment has a positive coefficient, but also failed to reach the level of statistical significance. Therefore, while the direction of the effect is consistent with H2, the lack of statistical significance doesn't allow for conclusive statements to be made based on this model. The combined treatment also has a positive coefficient, but

also failed to reach the level of statistical significance. H3 is not supported, although the effect is in the expected direction.

Model 2 excludes the interaction term between competence and benevolence, allowing for the direct testing of H3. The interaction coefficient is positive, therefore the effect of competence does seem to become more effective when accompanied by benevolence. However, the effect is still not statistically significant, which means that the conditional relationship outlined in H3 is not strongly supported.

Table 9: Regression results (full sample)

Variables	Model 1 (treatment)	Model 2 (no interaction)	Model 3 (+ Attitudes)	Model 4 (+Demographics)
Competence	-0.179 (0.492)	-0.139 (0.300)	-0.432 (0.419)	-0.329 (0.418)
Benevolence	0.226 (0.499)	0.028 (0.304)	-0.279 (0.432)	-0.282 (0.440)
Competence x Benevolence	0.411 (0.699)	-	0.601 (0.600)	0.503 (0.606)
Trust in government	-	0.349*** (0.078)	0.341*** (0.078)	0.315*** (0.078)
Familiarity with AI	-	-0.022 (0.087)	-0.025 (0.087)	0.026 (0.090)
Attitude toward AI	-	0.446*** (0.070)	0.453*** (0.071)	0.395*** (0.076)
Interest in politics	-	-0.083 (0.060)	-0.087 (0.060)	-0.112 (0.066)
Obs.:	210	210	210	210
R²:	0.009	0.296	0.299	0.365
Adjusted R²:	-0.005	0.275	0.275	0.301

F-test:	0.6362	14.2	12.32	5.747
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Note: Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Models 3 and 4 take additional covariates and demographic variables into consideration. These models serve as robustness checks and assess whether the estimated treatment effects remain stable when accounting for pre-existing individual characteristics.

Across these models the coefficients for competence and benevolence treatments continue to stay statistically insignificant. While competence remains to not be driving the support for AI, the benevolence in the extended models appears to gain a negative coefficient. The interaction term between the two dimensions of trust remains positive and statistically insignificant.

It is necessary to point out that several control variables in models 2 to 4 showed up as strong and consistent predictors of support for AI. For instance, baseline general trust in government is positively associated with support across all models in which it was included. Similarly, overall attitudes of respondents towards AI present a strong and statistically significant positive relationship with support for AI in the public sector.

5.4. Average treatment effects in the filtered sample

5.4.1. Descriptive statistics

The descriptive statistics for the filtered sample include values only for those respondents that passed the attention check questions following treatment exposure. The filtered sample consists of 163 observations. Interest in politics has a mean of 6.34. Trust in government shows a lower mean of 4.29. Familiarity with AI is relatively high with a mean of 7.37, while attitudes towards AI have a mean of 6.21.

For the key independent variables, perceived competence has a mean of 5.11, while perceived benevolence has a mean of 4.62. The dependent variable - support for AI - has a

mean of 5.85. Across all variables the minimum values range from 1 to 4, and the maximum reach up to 9 or 10, indicating that the full scale was utilized in most cases (Table B2, Appendix B).

5.4.2. Randomization and manipulation check

With the goal of evaluating the random assignment within filtered sample, baseline characteristics were also compared across four experimental groups: group A (high competence), group B (high benevolence), group C (high competence and benevolence), and group D (control) (Table B4, Appendix B).

With regards to attitudinal measures, group means show moderate variation but remain within comparable ranges. Interest in politics varies from 6.10 (SD = 2.76) in group A and 6.11 (SD = 2.60) in group D to 6.77 (SD = 2.22) in group C. Trust in government shows greater dispersion with the lowest mean of 3.78 in group B (SD = 1.80) and the highest in group C (5.11, SD = 1.91), while groups A and D report similar values (4.34 and 4.09). Familiarity with AI is relatively consistent across groups and ranges from 7.10 (SD = 1.48) to 7.71 (SD = 1.67). Attitudes toward AI present some variation with group D reporting lowest mean (5.61, SD = 2.36) and groups B and C higher values (6.71 and 6.69).

Gender distribution differs across groups to a greater extent than in the full sample. The proportion of male respondents ranges from 39% (group B) to 58.7% (group D), while female respondents constitute between 41.3% (group D) and 58.5% (groups A and B). Age composition is concentrated in the 18-24 and 25-34 categories across all groups, although the relative shares vary. The proportion of aged 18-24 ranges from 51.2% (group B) to 69.6% (group D), while the 25-34 group accounts for approximately $\frac{1}{3}$ of respondents in the treatment groups and a smaller share in group D (21.7%).

The field of study shows some imbalance across conditions. Group C has a higher proportion of non-STEM respondents (60%) and a lower share of STEM respondents (34.3%). Group D presents an opposite pattern with 54.3% of respondents being STEM students and 41.3% non-STEM. Groups A and B are evenly split between the two fields of study. Regarding the level of academic program, Bachelor's and Master's students constitute the majority across all groups (same as in the full sample). To take note, there is a higher concentration of doctoral students in group C. Most respondents are also from an urban upbringing, although the proportion is a bit lower in group C (80%) compared to groups A and B (87.8% and 92.7% respectively). Residency status is similar across all groups with group B including a higher proportion of non-residents of Kazakhstan (17.1%) compared to other groups.

The manipulation check analysis also highlights that the experimental manipulations produced differences in the respondents' perceptions of government competence and benevolence in the expected direction (Table B6, Appendix B). The greatest values are observed amongst the respondents in the group C with a mean of 5.94 (SD = 1.45) for perceived competence and a mean of 5.30 (SD = 1.93) for perceived benevolence. Respondents in groups A and B reported higher perceptions of both competence and benevolence relative to those in the control group.

Sample sizes are relatively balanced with 41 respondents in both groups A and B, 35 in group C, and 46 in group D.

5.4.3. Difference-in-means test

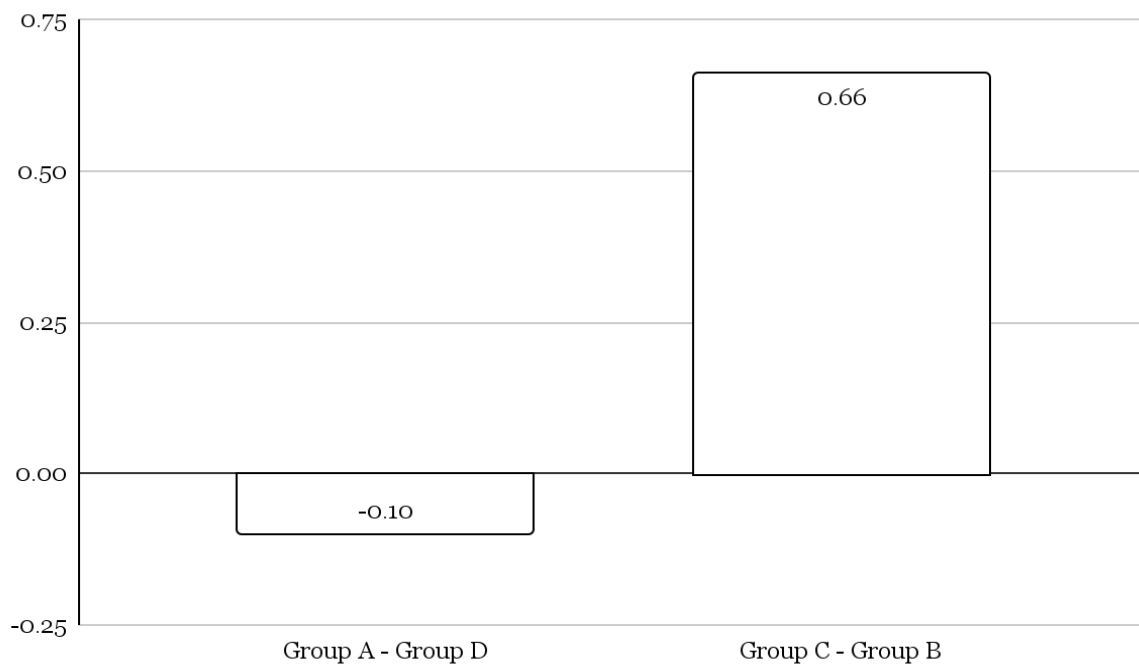
The examination of how support for AI varies across treatment groups within the filtered sample is accompanied by comparison of mean levels of outcome variable - support

for AI - across groups. Control group (D) serves as the reference category (Table B8, Appendix B).

The mean level of support for AI in the control group is 5.65. Across the treatment groups, group A has a mean of 5.55, group B = 5.82, and group C = 6.48. Relative to the control group, group A shows a difference of -0.10, while group B is associated with the difference of +0.17. Group C has a larger difference of +0.83.

Figure 2 presents pairwise comparison between selected treatment groups. The contrast between competence treatment group A and control group D is -0.10. The comparison between the combined treatment group C and the benevolence group B shows the difference of +0.66. As mentioned prior, the bar plot corresponds to the H3.

Figure 2: Treatment groups means differences (filtered sample)



5.4.4. Regression results

Carrying out a further assessment of the relationship between treatment conditions and support for AI, a series of OLS regression models were estimated using the filtered sample (Table 10). The models are specified to evaluate the robustness of the results: model 1 includes only treatment variables, model 2 excludes the interaction term and adds attitudinal controls, model 3 introduces interaction between competence and benevolence alongside attitudinal variables, and model 4 incorporates demographic controls.

In model 1 neither competence, nor benevolence shows statistically significant association with support for AI. The interaction term between competence and benevolence is also not statistically significant. The direction of an estimate for competence is negative, while benevolence and interaction terms are positive. Moreover, this model explains a rather small proportion of variance ($R^2=0.018$).

In model 2 competence and benevolence remain statistically insignificant and in the same direction as in model 1. Among the added variables, trust in government and attitude toward AI are positively and statistically significantly associated with support for AI. Familiarity with AI and interest in politics are not statistically significant. Introduction of attitudinal covariates substantially increases the explanatory power of model with $R^2=0.310$.

Table 10: Regression results (filtered sample)

Variables	Model 1 (treatment)	Model 2 (no interaction)	Model 3 (+ Attitudes)	Model 4 (+Demographics)
Competence	-0.103 (0.566)	-0.100 (0.357)	-0.383 (0.481)	-0.365 (0.490)
Benevolence	0.165 (0.566)	0.141 (0.361)	-0.150 (0.491)	-0.287 (0.520)
Competence x Benevolence	0.772 (0.830)	-	0.626 (0.713)	0.672 (0.741)
Trust in government	-	0.374*** (0.091)	0.361*** (0.092)	0.346*** (0.095)
Familiarity with AI	-	-0.079 (0.105)	-0.084 (0.106)	-0.011 (0.111)
Attitude toward AI	-	0.449*** (0.083)	0.456*** (0.083)	0.396*** (0.090)
Interest in politics	-	-0.115 (0.070)	-0.117 (0.071)	-0.119 (0.077)
Obs.:	163	163	163	163
R²:	0.018	0.310	0.313	0.364
Adjusted R²:	-0.001	0.2833	0.282	0.289
F-test:	0.945	11.67	10.100	4.875

Note: Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

In model 3 similar dynamics are visible as in models 1 and 2: competence and benevolence, as well as their interaction term remain statistically insignificant. Yet the direction of estimates differs for benevolence, turning negative as seen in the regression results for the full sample. Model 4 follows the same path as model 3, yet with a slightly increased explanatory power. In model 3 the regression explained 31.3% of the variance, while in model 4 it is equal to 36.4%. Trust in government and attitude toward AI continue to

be the only variables that show statistically significant association with support for AI in the public sector.

5.5. Conclusion

This chapter presented the empirical findings of the study, drawing on both the full and filtered samples to assess the effects of experimentally manipulated perceptions of competence and benevolence on support for AI in the public sector. Across the difference-in-means analysis, variation in average levels of support for AI between treatment and control groups was observed. However, these differences didn't reach necessary levels of statistical significance.

The regression analysis further evaluated these relationships through a series of earlier specified models. In both the full and filtered samples the competence treatment didn't show the statistically significant effect on support for AI and the coefficient went in a negative direction as opposed to the expectations, therefore there isn't empirical support for H1. The benevolence treatment showed a positive but statistically insignificant coefficient, offering limited alignment with H2. In extended models the coefficient for benevolence became negative, though still statistically insignificant.

The interaction between competence and benevolence was consistently positive across all models in both samples. This indicates that the joint presence of these variables is associated with higher support for AI in the public sector, however the interaction term still didn't achieve statistical significance, meaning that H3 is not supported by the empirical evidence.

In contrast, several control variables emerged as strong and consistent predictors of support for AI. Trust in government and general attitudes towards AI were positively and

statistically significantly associated with the dependent variable across all models where they were included. Other controls didn't show statistical significance.

The following chapter situates these findings within the theoretical framework developed earlier, addressing their implications, potential explanations, and limitations.

Chapter 6: Discussion

6.1. Introduction

This chapter discusses the findings of the study with regards to the developed theory and existing scholarly works on the topic. The structure goes as follows. The chapter begins by interpreting the main results by focusing on how they relate to the expected relationships between perceived competence, benevolence, and support for AI in the public sector. Next, there is an outline of the theoretical implications of findings with emphasis made on how they refine existing understandings of trust in government and its role in shaping attitudes toward AI.

Furthermore, the chapter includes a substantive interpretation of the results, highlighting their relevance for real world policymaking contexts. The limitations of the study's findings are also appropriately addressed with suggestions for future research.

6.2. Interpretation of main findings

The findings of this study imply that informational cues about government performance have limited capacity in independently shaping citizen support for AI in public services. Across both the full and filtered samples, none of the treatments achieved statistical significance in any of the estimated models. This indicates that such short-term experimentally manipulated perceptions alone don't produce strong causal effects.

While the absence of statistically significant effects means that the hypotheses are not empirically supported, the observed patterns remain theoretically informative when interpreted with regards to the theoretical framework developed in Chapter 3. The results don't contradict the core theoretical expectation that trust in government shapes support for AI. Specifically, they suggest that dimensions of trust in government operate at a deeper level than can be influenced through isolated informational treatments.

The findings do reinforce the argument that AI in the public sector is evaluated not as an autonomous object, but as an extension of government authority. As mentioned in the theoretical framework, citizens rely on broader institutional evaluations when forming attitudes toward algorithmic governance. The strong and consistent statistical significance of baseline trust in government across all models, in which this variable was included, provides direct evidence-based support for this claim. As opposed to responding to the experimental high competence and/or benevolence treatment, respondents were found to be relying on pre-existing levels of political trust when assessing the desirability of AI in public services.

The behavior of the benevolence variable further supports such interpretation (H2). In simpler models benevolence was presented as having more positive association with support for AI than competence, even though it did not reach statistical significance. This pattern was visible in models 1 and 2, yet the coefficient for benevolence turned negative once attitudinal and demographic control variables were added. This might be explained by the following. The correlation matrix shows that benevolence and baseline trust in government are relatively strongly correlated (Figure B1, Appendix B). It may be possible that once the variable of trust in government was included, it took on the majority of explanatory power that the benevolence had in simpler models. Hence, it may be stated that benevolence doesn't independently increase support for AI in the public sector in the case when broader trust in government is accounted for.

When it comes to competence, a different dynamic is observed. The consistently non-significant and negative coefficients indicate that emphasizing government competence alone doesn't translate into increased support for AI. This finding challenges the idea that technical expertise and administrative effectiveness are sufficient enough to legitimize the use of algorithm-driven tools in governance (H1). Instead, it seems evident that competence

treatment may lack persuasive power, especially in domains characterized by uncertainty and limited transparency such as AI.

An additional interpretation of the negative coefficient associated with perceived competence might be connected to how citizens evaluate the necessity of AI in governance. When a government is perceived as highly competent, individuals may think that the existing administrative and technical capacity of the state is already sufficient for effective policy implementation and service delivery. Hence, the introduction of AI in the public sector may not be viewed as an enhancement, but as an unnecessary step. Rather than increasing support, higher perceived competence may reduce the need for technological advancement with AI, therefore resulting in lower levels of support for AI in public services.

The interaction term's coefficient remains consistently positive across all models, although not reaching statistical significance. It should be noted that the direction of an estimate highlights the presence of conditional relationship between two dimensions of trust (H3). This finding aligns with expectations set up in the theoretical framework, according to which citizens require benevolent intentions of the government to legitimize the use of AI technologies in the public sector.

The most statistically significant findings were related to pre-existing attitudes of respondents. Baseline trust in government and general attitudes towards AI were found as the strongest predictors of support across all regression models. Such empirical evidence backs up an understanding earlier discussed in the literature review and theoretical framework chapters that citizen support for AI is structured by a combination of institutional trust and technological attitudes, both of which precede and outweigh the influence of short-term informational manipulations.

6.3. Theoretical implications

To reiterate, the empirical results of this study don't provide statistically significant support for the hypothesized direct effects of competence and benevolence. However, they still contribute to refining and extending the theoretical framework developed in this thesis.

For example, the results underline the importance of trust dimensions in shaping the support for the deployment of AI-driven tools in governance. The strong and consistent effect of baseline trust in government across all regression models suggests that citizens do rely on pre-existing institutional evaluations when forming attitudes toward AI in public services. This finding allows to further extend the argument by stating that trust in government should be conceptualized more comprehensively and structurally to align with perspectives that emphasize the social embeddedness feature of AI in the public sector.

Moreover, the results do not invalidate the assumption that the separate dimensions of trust - competence and benevolence - can be empirically isolated as independent causal drivers in the form presented in this study. On the contrary, the study demonstrates that these dimensions can be conceptually and empirically distinguished and that they produce effects in the expected direction. This has implications for further research: the findings suggest the need for further research in this direction with larger samples and more refined operationalization strategies.

Additionally, the consistently positive interaction between competence and benevolence provides preliminary support for the argument that trust dimensions function in a conditional manner rather than independently. This goes in line with the recent scholarship in the field that underlines that citizens evaluate government actions through combined assessment of capability and intentions. The findings suggest that competence without benevolence may lack influencing power. Although the effect didn't reach statistical

significance, its direction and stability offers the possibility to accept H3 as plausible and calls for further research of the matter.

The results also contribute to the existing literature on citizen attitudes toward AI in the public sector in such a way that they demonstrate the intertwined nature of the relationship between technology-related evaluations and political opinions. The strong effect of general attitudes toward AI shows that support for AI in governance is indeed reflective of broader perceptions toward technological advancements. In order to not overlook the interaction between technology-based trust and institutional trust, it is vital to look into more integrative theoretical models in future research projects.

It is also important to note that the findings of this thesis contribute to the existing literature by demonstrating the importance of disaggregating trust in government into its constituent dimensions rather than treating it as a unified construct. By distinguishing between perceived competence and benevolence, this study highlights that the citizens' attitudes toward AI in public services are shaped through a more nuanced prism of trust in government. Such an approach paves a way for future researchers as it shows that public opinion towards AI may be and should be examined through dimensions of institutional trust. In this context, the findings of the thesis also can serve as an explanation for mixed or contradictory findings in contemporary scholarship on the topic: inconsistencies might stem from insufficiently broken down conceptualizations of trust in government.

6.4. Substantive interpretation and policy implications

The findings of the given study indicate that citizen acceptance of AI in the public sector is grounded in broader perceptions of government and technology. In practical terms, this suggests that people interpret digital innovations in governance through an already established set of attitudes. Within the context of Kazakhstan, this result is particularly useful.

The initiatives to incorporate AI-driven technologies in public services, especially in the public safety domain, are likely to not be perceived as mere modernization efforts, but rather as a part of further state development and extension of control. With the public perceptions of AI being embedded in existing relationships between citizens and government, it is safe to say that the success of AI-driven reforms depends less on how the state presents the initiative, but mostly on how the state is perceived in the long term.

The lack of findings supporting the hypothesis on the positive effect of competence on support for AI implies that emphasizing technical efficiency and administrative effectiveness of the government is ineffective in driving public acceptance. Such narratives are often at the core of the state's communication agendas, however they may not resonate strongly with the general public. In contrast, the positive direction of perceived benevolence signals that people are quite attentive to why the government is implementing certain initiatives. Although statistical insignificance of benevolence-related estimates suggests that attempts to frame AI deployment in the public sector as beneficial and citizen-centered may be limited in their persuasive power, it is nonetheless important to take this dimension into consideration when crafting the policy implementation plan.

From a policy perspective, findings of the study emphasize the need for substantial attention to be paid to the institutional environment in which the technology is planned to be introduced. In particular, it is vital to strengthen transparency, ensure accountability, and demonstrate consistent alignment with public interests to foster acceptance of algorithm-driven systems in the public sector. The results also highlight that policymakers should recognize the role of general perceptions toward new technologies such as AI. In this context, the successful implementation of the latter necessitates addressing concerns directly and in a timely manner, rather than treating technological benefits as self-evident.

6.5. Limitations

It is necessary to address several limitations of the study when interpreting its results. First, the use of the student sample may limit the external validity of presented results. The sample is relatively young and educated, which may lead to higher familiarity with AI and more homogenous attitudes as opposed to the general population. Hence, the observed relationships are not fully generalizable to broader society, particularly those with lower exposure to technologies or different levels of political engagement.

Second, apart from the external validity, it is necessary to take into account that the small sample size is the primary limitation of this study. It can be stated that it is most likely that the sample size has reduced the statistical significance of the results, because the observed relationships generally emerged in the expected direction. Thus, it is expected that a larger and more diverse sample would provide greater variation in attitudes and increase the likelihood of observing statistically significant effects. With that in mind, the findings should not be interpreted as evidence against the proposed hypotheses, but rather as a preliminary data that requires further testing on a broader scale.

Third, it should be noted that the study was conducted within a specific political context of Kazakhstan, characterized by limited transparency and features of an authoritarian regime. As discussed in the theoretical framework chapter, such conditions may affect how perceived dimensions of trust are reported, thus influencing how citizens respond to survey questions and experimental treatments. Nonetheless, this context provides valuable insights into AI governance in non-democratic settings, despite the results characterizing as rather limited in their generalizability to other political systems.

6.6. Conclusion

This chapter examined the findings of the study through the lens of the theoretical framework and existing literature in the field. The analysis shows that support for AI is based on broader perceptions of people regarding the government and new technologies. The findings do reinforce the central argument that the acceptance of AI in governance is a socially embedded notion.

It was explicitly emphasized that the dimensions of trust were found to not be operating in isolation. Their effects appear to be intertwined between themselves and with respect to specific socio-political contexts in which AI-driven technology is implemented. The discussion also emphasized how efforts to drive the acceptance of AI in public services should be accompanied by assessment of institutional conditions and modifying the communication strategies to address questions of legitimacy, credibility, and citizen perceptions.

Overall, it has been demonstrated that understanding public support for AI requires a comprehensive approach which integrates trust dimensions, technology-related attitudes, and contextual factors. By achieving that, this study contributes to the existing literature on understanding how citizens evaluate AI in governance and outlines attention worthy directions for policy development and further research.

Chapter 7: Conclusion

The growing use of AI in the public sector reflects a shift in global governance practices. This is largely due to the nature of AI - a distinct form of technological development, which has not been yet fully assessed itself. A substantial part of contemporary scholarly works have been focusing on the mentioned specification of AI and other technical characteristics of such systems in assessing factors that drive people's support for them. However, a limited body of research was produced regarding the institutional factors, which may shape how individuals perceive AI-driven initiatives in the public sector. This thesis aimed at tackling the mentioned limitation by suggesting that public support for AI in governance is grounded in pre-existing beliefs that people hold regarding the state.

The empirical findings presented in this thesis provide clear evidence that perceptions of government do indeed play a role in shaping attitudes towards AI. In line with the formulated hypotheses, perceived benevolence was found to be positively associated with support for AI in the public sector and exhibited a conditioning effect on the dimension of perceived competence. While general attitudes toward AI appeared as statistically significant determinants of support for AI in the public sector, more comprehensive analysis of the findings reinforces the idea that the support for AI in governance can not be understood from a merely technology-driven standpoint. When applied in the public sector, AI is not to be treated as a neutral digital advancement, but rather as an extension of government itself.

Most importantly, the findings of this study demonstrate that the dimension of perceived benevolence occupies a central role in shaping public acceptance of AI in governance. In particular, its critical importance is especially evident when it involves the dimension of perceived competence as the latter becomes insignificant in the absence of benevolence. In more practical terms, this study firmly grounds an understanding that benevolence is not merely an additional factor among many, but a necessary condition for

citizen support for AI in the public sector. Hence, it is clear that people need to believe that AI's implementation is accompanied by benevolent intentions of the government as a whole.

The insights of the study carry important implications for future research. Primarily, they highlight the empirical potential for more integrated theoretical frameworks to be developed in bridging the gap between political trust and AI acceptance literature. Moreover, the study emphasizes the presence of an insufficiency in scholarly investigations on the topic of how different dimensions of trust interact between each other, especially in the political contexts of contested institutional legitimacy. It also invites the researchers to explore alternative or expanded versions of the presented research design and methodology to evaluate the mentioned relationships.

An important direction for future research concerns the context-dependent nature of AI in the public sector. As noted in the literature review of this thesis, public attitudes towards AI are not uniform and vary depending on the specific domain in which the technology is deployed. This study presented AI to the respondents by outlining a surveillance-related case, particularly one where an AI-backed facial recognition feature is added to the “Sergek” system. While this context is policy relevant and realistic, it is also associated with heightened concerns for privacy, control, and state authority. As a result, the findings of the thesis may reflect not only general attitudes towards AI in public services, but also citizens' reactions to surveillance itself. Future studies would therefore benefit from examining a broader range of AI use in public services (for example, in administrative automation, welfare distribution, or healthcare assistance) to assess how the support for AI varies across policy domains.

Another avenue for future research is related to the potential urban-rural divides in attitudes towards AI in the public sector. The sample used in this study is predominantly composed of respondents from urban areas of upbringing, where exposure to digital technologies and government-led innovation is comparatively higher. However, those who

grew up in rural areas, where infrastructural development and access to technologies is limited, may hold different expectations regarding the feasibility and relevance of AI implementation. In this context, individuals might be less inclined to view AI as a realistic component of public service delivery, which in turn could shape their level of support for such technologies. With this in mind, future studies should account for geographical disparities by, perhaps, incorporating more balanced samples or conducting comparative analyses between urban and rural populations. This would allow for a formation of a more comprehensive understanding of how contextual factors influence the acceptance of AI in public services.

Additionally, the study brings up significant practical implications for policymakers. As mentioned previously, the findings indicate that policymakers should place particular emphasis on strengthening perceptions of governmental benevolence when introducing AI in the public sector. Since benevolence reflects the belief that the government acts in the interest of the public and prioritizes citizens' well-being, the implementation of AI technology should be framed as a citizen-oriented initiative designed to improve public welfare. This requires the governing structures to ensure that AI tools are introduced in ways that are transparent, inclusive, and responsive to public concerns. For instance, clear communication about the purpose of such systems, the expected benefits to the public, and safeguards against misuse may help to mitigate concerns and fears that such technologies are going to be implemented primarily for surveillance and expansion of control at the expense of citizens' rights. Thus, policymakers should prioritize developing effective communication strategies with the public.

The governments also should adopt practices that strengthen participatory action with regards to AI implementation. In saying that, it is necessary to hold public consultations, citizen forums, collaboration with civil society and non-governmental organizations in order to express that societal interests are at the core of AI initiatives. However, the participation of the public should not be treated and carried out as symbolic, as it may backfire by drastically

lowering the overall trust in government and its legitimacy in the eyes of citizens. On the contrary, the realization of participatory initiatives would benefit only if it is integrated into the decision-making process. This is especially important in the contexts where AI is planned to be introduced in sensitive policy areas such as public safety, welfare distribution, or healthcare.

Important implications can also be drawn with regards to accountability and institutional safeguards. It is essential to make sure that there are independent oversight mechanisms, which are capable of monitoring how AI tools are used in the public sector. Namely, independent ethics committees, external auditing processes, and open evaluation reports by unbiased non-governmental human rights organizations may contribute by signaling the benevolent intentions of the government and commitment to non-exploitative use of algorithm-driven technology in the delivery of public services.

Above all, there is a need for crafting a policy, which is oriented towards reducing informational inequality. The findings clearly showed the significance of general attitudes toward AI in shaping support for such technology in public services, therefore, governments should be tasked with increasing investments in programs aimed at raising the technological literacy of citizens. Failure to address inequality in familiarity with AI may lead to not only resistance toward AI implementation, but also to heightening of social inequalities amongst the citizens themselves. Furthermore, it is vital to support projects that focus on researching the topic of this thesis as they may contribute significantly to the successful implementation of AI in the public sector by identifying more intricate relationships between factors affecting the support for algorithmic technology.

All in all, this study puts forward the following central point: acceptance of AI in governance doesn't happen in vacuum. It is fostered through the prism of citizens' beliefs about the state, its capabilities and intentions. Thus, successful implementation of AI in the

public sector doesn't solely depend on the advancements in technology itself, but is directly reflective of the relationship between the government and citizens. In this context, the given thesis contributes to a more nuanced understanding of AI-driven governance, which recognizes trust as a foundational condition for its realization and success.

Reference List

- Aoki, No. 2020. "An Experimental Study of Public Trust in AI Chatbots in the Public Sector." *Government Information Quarterly* 37 (4): 101490.
- Alhosani, K., and Alhashmi, S. M.. 2024. "Opportunities, Challenges, and Benefits of AI Innovation in Government Services: A Review." *Discover Artificial Intelligence* 4 (1): 18.
- Afroogh, S., Akbari, A., Malone, E., Kargar, M. and Alambeigi, H. 2024. "Trust in AI: Progress, Challenges, and Future Directions." *Humanities and Social Sciences Communications* 11 (1): 1–30.
- Bhattacharjee, A. 2012. *Social Science Research: Principles, Methods, and Practices*. Tampa: University of South Florida.
- Braun, S., Peus, C., Weisweiler, S., and Frey, D. 2013. "Transformational Leadership, Job Satisfaction, and Team Performance: A Multilevel Mediation Model of Trust." *The Leadership Quarterly* 24 (1): 270–283.
- Campbell, J. W. 2023. "Public Participation and Trust in Government: Results from a Vignette Experiment." *Journal of Policy Studies* 38 (2): 23–31.
- Charles, V., Rana, N. P. and Carter, L. 2022. "Artificial Intelligence for Data-Driven Decision-Making and Governance in Public Affairs." *Government Information Quarterly* 39: 1–4.
- Chen, K. Y., and Wen, C. R. 2021. "Impacts of Attitudes toward Government and Corporations on Public Trust in Artificial Intelligence." *Communication Studies* 72 (1): 115–131.
- DeSouza, K. C., Dawson, G. S., and Chenok, D. 2020. "Designing, Developing, and Deploying Artificial Intelligence Systems: Lessons from and for the Public Sector." *Business Horizons* 63: 205–213.
- Devine, D., Valgarðsson, V., Jennings, W., Stoker, G., and Bunting, H.. 2025. "The Causes of Perceived Government Trustworthiness." *European Journal of Political Research* 64 (3): 1394–1412.
- Druckman, J. N., and Kam, C. D. 2011. "Students as Experimental Participants." In *Cambridge Handbook of Experimental Political Science*, 41–57.
- Dunn, J. R., and Schweitzer, M. E. 2005. "Feeling and Believing: The Influence of Emotion on Trust." *Journal of Personality and Social Psychology* 88 (5): 736–748.
- Frazier, M. L., Johnson, P. D., and Fainshmidt, S. 2013. "Development and Validation of a Propensity to Trust Scale." *Journal of Trust Research* 3 (2): 76–97.
- Freedom House. 2025. "Kazakhstan: Freedom in the World 2025 Country Report." <https://freedomhouse.org/country/kazakhstan/freedom-world/2025>
- Glikson, E., and Woolley, A. W. 2020. "Human Trust in Artificial Intelligence: Review of Empirical Research." *Academy of Management Annals* 14 (2): 627–660.

Grimmelikhuijsen, S. 2010. "Transparency of Public Decision-Making: Towards Trust in Local Government?" *Policy & Internet* 2 (1): 5–35.

Grimmelikhuijsen, S. 2012. "Linking Transparency, Knowledge and Citizen Trust in Government: An Experiment." *International Review of Administrative Sciences* 78 (1): 50–73.

Grimmelikhuijsen, S., and Knies, E. 2017. "Validating a Scale for Citizen Trust in Government Organizations." *International Review of Administrative Sciences* 83 (3): 583–601.

Haesevoets, T., Verschuere, B., Van Severen, R., and Roets, A.. 2024. "How Do Citizens Perceive the Use of Artificial Intelligence in Public Sector Decisions?" *Government Information Quarterly* 41 (1): 101906.

Hardin, R.I. 2013. "Government without Trust." *Journal of Trust Research* 3 (1): 32–52.

Hansen, F. G. 2023. "Can Warm Behavior Mitigate the Negative Effect of Unfavorable Governmental Decisions on Citizens' Trust?" *Journal of Experimental Political Science* 10 (1): 62–75.

Heinrichs, B. 2022. "Discrimination in the Age of Artificial Intelligence." *AI & Society* 37 (1): 143–154.

Henman, P. 2020. "Improving Public Services Using Artificial Intelligence: Possibilities, Pitfalls, Governance." *Asia Pacific Journal of Public Administration* 42 (4): 209–221.

Hooghe, M. 2011. "Why There Is Basically Only One Form of Political Trust." *The British Journal of Politics and International Relations* 13 (2): 269–275.

Houston, D. J., and Harding, L. H. 2013. "Public Trust in Government Administrators: Explaining Citizen Perceptions of Trustworthiness and Competence." *Public Integrity* 16 (1): 53–76.

Kitt, S., Axsen, J., Long, Z., and Rhodes, E. 2021. "The Role of Trust in Citizen Acceptance of Climate Policy: Comparing Perceptions of Government Competence, Integrity and Value Similarity." *Ecological Economics* 183: 106958.

Kleizen, B., Van Dooren, W., Verhoest, K., and Tan, E. 2023. "Do Citizens Trust Trustworthy Artificial Intelligence? Experimental Evidence on the Limits of Ethical AI Measures in Government." *Government Information Quarterly* 40 (4): 101834.

Kostka, G., Steinacker, L., and Meckel, M. 2023. "Under Big Brother's Watchful Eye: Cross-Country Attitudes toward Facial Recognition Technology." *Government Information Quarterly* 40 (1): 101761.

Lean, O. K., Zailani, S., Ramayah, T., and Fernando, Y. 2009. "Factors Influencing Intention to Use E-Government Services among Citizens in Malaysia." *International Journal of Information Management* 29 (6): 458–475.

- Liu, L., Vrieling, L., Perlaviciute, G., Bouman, T., and Steg, L. 2022. "The Role of Trust in Public Acceptability of Energy Projects: Integrity versus Competence." *Environmental Research Communications* 4 (3): 035003.
- Mayer, R. C., Davis, J. H., and Schoorman, F. D. 1995. "An Integrative Model of Organizational Trust." *Academy of Management Review* 20 (3): 709–734.
- McKnight, D. H., Choudhury, V., and Kacmar, C. 2002. "The Impact of Initial Consumer Trust on Intentions to Transact with a Web Site: A Trust Building Model." *Journal of Strategic Information Systems* 11 (3–4): 297–323.
- Mellouli, S., Janssen, M., and Ojo, A. 2024. "Introduction to the Issue on Artificial Intelligence in the Public Sector: Risks and Benefits of AI for Governments." *Digital Government: Research and Practice* 5 (1): 1–6.
- Mergel, I., Dickinson, H., Stenvall, J., and Gascó, M. 2024. "Implementing AI in the Public Sector." *Public Management Review* 0 (0): 1–14.
- Otting, S. K., and Maier, G. W. 2018. "The Importance of Procedural Justice in Human–Machine Interactions: Intelligent Systems as New Decision Agents in Organizations." *Computers in Human Behavior* 89: 27–39.
- Prahl, A., and Van Swol, L. M. 2017. "Understanding Algorithm Aversion: When Is Advice from Automation Discounted?" *Journal of Forecasting* 36: 691–702.
- Schnackenberg, A. K., and Tomlinson, E. C. 2016. "Organizational Transparency: A New Perspective on Managing Trust in Organization-Stakeholder Relationships." *Journal of Management* 42 (7): 1784–1810.
- Schnell, T., and Schmidt-Scheele, R. 2025. "The Social Embeddedness of Trust in AI: How Existing Trust Relations to Decision-Makers and Institutions Influence Trust in AI Decision Aids for Public Administration." *GEIST Working Paper Series* (02).
- Slade, G., Trochev, A., and Talgatova, M. 2022. "The Limits of Authoritarian Modernisation: Zero Tolerance Policing in Kazakhstan." In *Justice, Crime, and Citizenship in Eurasia*, ed. Erica Marat and Laurie A. McCarthy, 178–199. Oxon and New York: Routledge.
- Susar, D., and Aquaro, V. 2019. "Artificial Intelligence: Opportunities and Challenges for the Public Sector." In *Proceedings of the 12th International Conference on Theory and Practice of Electronic Governance*, 418–426.
- Thiebes, S., Lins, S., and Sunyaev, A. 2021. "Trustworthy Artificial Intelligence." *Electronic Markets* 31 (2): 447–464.
- Valle-Cruz, D., Garcia-Contreras, R., and Gil-Garcia, J. R. 2024. "Exploring the Negative Impacts of Artificial Intelligence in Government: The Dark Side of Intelligent Algorithms and Cognitive Machines." *International Review of Administrative Sciences* 90 (2): 353–368.
- Vereschak, O., Bailly, G., and Caramiaux, B. 2021. "How to Evaluate Trust in AI-Assisted Decision Making? A Survey of Empirical Methodologies." *Proceedings of the ACM on Human-Computer Interaction* 5 (CSCW2): 1–39.

Vereschak, O., Alizadeh, F., Bailly, G., and Caramiaux, B. 2024. “Trust in AI-Assisted Decision Making: Perspectives from Those Behind the System and Those for Whom the Decision Is Made.” In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, 1–14.

Wirtz, B. W., Weyerer, J. C., and Geyer, C. 2019. “Artificial Intelligence and the Public Sector - Applications and Challenges.” *International Journal of Public Administration* 42 (7): 596–615.

You, J. 2018. “Trust and Corruption.” In *The Oxford Handbook of Social and Political Trust*, ed. Eric M. Uslaner, 473–496. Oxford: Oxford University Press.

Zuiderwijk, A., Chen, Y., and Salem, F. 2021. “Implications of the Use of Artificial Intelligence in Public Governance: A Systematic Literature Review and a Research Agenda.” *Government Information Quarterly* 38: 1–19.

Appendices

Appendix A. Survey

A.1.1. Questionnaire (English version)

Trust in Government and Support for AI in Public Services

BLOCK 1: DEMOGRAPHICS

1. What is your age?

- ☐ 18 – 24
- ☐ 25 – 34
- ☐ 35 – 44
- ☐ 45 – 54
- ☐ 55 – 64
- ☐ 65 or older

2. What is your gender?

- ☐ Female
- ☐ Male
- ☐ Other: ____
- ☐ Prefer not to say

3. Are you currently a citizen / permanent resident of Kazakhstan?

- ☐ Yes
- ☐ No

4. What type of place did you grow up in?

- ☐ Urban area
- ☐ Rural area

5. Which academic program are you currently enrolled in?

- ☐ Foundation Year
- ☐ Bachelor's
- ☐ Master's
- ☐ Doctoral
- ☐ Other: ____

6. Which best describes your field of study?

- ☐ STEM
- ☐ Non-STEM

☐ Not sure

BLOCK 2: POLITICAL INTERESTS

7. How interested would you say you are in politics? Rate from 1 to 10:

1	2	3	4	5	6	7	8	9	10
Not at all interested									Very interested

8. Overall, how much do you trust the government? Rate from 1 to 10:

1	2	3	4	5	6	7	8	9	10
Do not trust at all									Completely trust

BLOCK 3: ARTIFICIAL INTELLIGENCE

9. How familiar are you with AI (artificial intelligence) technologies? Rate from 1 to 10:

1	2	3	4	5	6	7	8	9	10
Not at all familiar									Very familiar

10. Overall, how do you feel about AI (artificial intelligence)? Rate from 1 to 10:

1	2	3	4	5	6	7	8	9	10
Very negative									Very positive

BLOCK 4: VIGNETTE

11. Please, read the following information carefully:

Vignette A: Competence Level Manipulation – Group 1

Over the past decade Kazakhstan's government has consistently demonstrated strong administrative and technical capacity in implementing complex reforms and managing large-scale public programs. Major national initiatives have been executed according to clearly defined strategic plans with centralized coordination across ministries and akimats (local administration).

Government institutions have successfully modernized infrastructure in multiple public service sectors, integrating digital and administrative systems to improve speed, accuracy, and coordination. In 2022 the centralized platform "e-Otinish" was launched to streamline communication between citizens and state institutions. The platform enables users to submit appeals, track case progress, file complaints, and initiate legal claims without visiting state institutions. By the end of 2025, more than 5 million appeals have been processed with the vast majority (90%) being responded to within minimal deadlines (few hours to 3 days).

Public service delivery has further been supported by centralized administrative platforms using automated verification systems and standardized processing protocols, resulting in rapid review times and exceptionally high levels of procedural accuracy, according to independent external audits conducted in 2025 by "Deloitte" and "PwC" firms.

Government agencies also demonstrated a high level of coordination in managing import and export processes, contributing to the efficient implementation of national trade objectives. Through structured interdepartmental communication, precise allocation of logistical resources, and timely execution of administrative procedures, agencies ensured consistent operational performance. As a result, total trade turnover reached \$150 billion in 2025, exceeding levels observed over the previous five years.

Vignette B: Benevolence Level Manipulation – Group 2

Over the past decade, the government of Kazakhstan has consistently emphasized that public policy should prioritize well-being, dignity, and long-term security of its citizens. National development strategies have repeatedly highlighted social protection, equal access to opportunities, and support for vulnerable groups as central policy objectives.

To ensure that public opinion reaches state institutions, feedback mechanisms have been established across the country. Public forums and listening sessions have been held in both urban and rural areas, where citizens were able to openly share their concerns and community needs. As the result, the government adjusted public welfare programs and initiated new policies and projects, aimed at prioritizing the vulnerable social groups, as well as the population at large. A public opinion poll conducted by the "Pew Research Center" in 2025 found that 78% of respondents felt that "the government genuinely cares about the well-being of people like me" while 82% said they believed the government policies reflect citizens' interests above all else.

Notably, the government demonstrated strong concern for citizens during the 2024 floods that affected the majority of regions in Kazakhstan. In addition to providing financial assistance and conducting rescue operations, the state established support hotlines offering psychological assistance to the affected citizens. Surveys conducted afterwards indicated that many citizens viewed these measures as evidence of the government's commitment to protect the well-being of people during times of crisis.

Vignette C: Competence and Benevolence Level Manipulation – Group 3

Over the past decade, the Government of Kazakhstan has demonstrated a consistently high level of administrative and technical capacity while maintaining a strong commitment to protecting citizens' well-being. Major reforms have been implemented according to clearly defined strategic plans, supported by coordinated efforts across ministries and akimats (local administration).

Government initiatives have expanded targeted assistance programs for low-income families, rural communities, and individuals facing economic hardship. Social support mechanisms have been strengthened to ensure that benefits reach those most in need, with regular public reporting aimed at increasing transparency and accountability. As the result, by the end of 2025 the amount of people living below the poverty line dropped from 5.1% to 1%.

During periods of crisis, authorities have publicly committed to protecting citizens from economic and social risks, introducing relief measures designed to reduce financial burdens on households and small businesses. For example, after the 2024 floods in several regions expedited procedures were launched to deliver financial assistance to the affected population without bureaucratic delays, allowing the people to collect funds within few days after the incident. Public consultations and feedback mechanisms have also been expanded to allow citizens to voice concerns. During and after the floods direct communication lines were established, through which people had an opportunity to resolve their issues within unprecedentedly short periods of time – from few hours to 3 days.

Vignette D: No Manipulation – Group 4

The Winter Olympic Games are a major international sporting event that brings together athletes from around the world to compete in a wide range of disciplines. The 2026 Winter Olympics were hosted by Milan and Alpine mountain resort town of Cortina d'Ampezzo in Italy, featuring competition across sports such as ice hockey, figure skating, biathlon, bobsleigh, alpine skiing, cross-country skiing, freestyle skiing, snowboarding, short track speed skating, curling, luge, Nordic combined, skeleton, ski mountaineering, ski jumping.

The 2026 Games brought together participants from 93 countries. Delegations from European, American, and Asian countries were the largest in terms of the participating athletes. Norway, USA, Netherlands, Italy, and Germany secured the highest number of medals. Brazil was the country closest to equator to win a medal.

The oldest medalist in the 2026 Olympic Games was a 46-year old Silvana Tirinzoni, a winner of the silver medal in women's curling from Switzerland. The youngest medalist was from the Republic of Korea – 17-year old Choi Gaon, who secured gold in the women's snowboarding halfpipe. Moreover, these Games were referred to as the most gender-balanced Winter Olympics in history with women making up 47% of all athletes.

12 (A). According to the information above, which global firms conducted independent audits of centralized administrative platforms in 2025? (only respondents from Group 1 answer this question)

- ☐ KPMG and EY
- ☐ McKinsey and BCG
- ☐ Deloitte and PwC
- ☐ BDO and RSM

12 (B). According to the information above, which international public opinion organization conducted a poll in Kazakhstan in 2025? (only respondents from Group 2 answer this question)

- ☐ Pew Research Center
- ☐ Gallup World Poll
- ☐ World Values Survey
- ☐ Ipsos

12 (C). According to the information above, how fast were people's issues' resolved during and after the floods of 2024? (only respondents from Group 3 answer this question)

- ☐ Few minutes
- ☐ Few hours to 3 days
- ☐ Several months
- ☐ None of the above

12 (D). According to the information above, how many countries participated in the 2026 Winter Olympic Games? (only respondents from Group 4 answer this question)

- ☐ 84 countries
- ☐ 93 countries
- ☐ 155 countries
- ☐ 77 countries

BLOCK 6: MANIPULATION CHECK

13. How effective do you think the government is in dealing with problems in our country? Rate from 1 to 10:

1	2	3	4	5	6	7	8	9	10
Not effective at all									Extremely effective

14. How would you rate the government's technical and administrative capacity to implement reforms and carry out policies? Rate from 1 to 10:

1	2	3	4	5	6	7	8	9	10
Very low									Very high

15. How much do you think the government cares about the well-being of people?
Rate from 1 to 10:

1	2	3	4	5	6	7	8	9	10
Not at all									Very much

16. To what extent do you believe the government is motivated to act in the best interest of people? Rate from 1 to 10:

1	2	3	4	5	6	7	8	9	10
Not at all									To a very great extent

BLOCK 7: AI IN PUBLIC SERVICE

17. Please, read the following information carefully and answer the questions below:

In the recent years Kazakhstan has implemented digital monitoring technologies to improve public safety and traffic management. One example is the “Sergek” system, which has been deployed in major cities to monitor road traffic and detect violations such as speeding or running red lights. The system relies on AI-powered video analytics to automatically identify traffic offenses and generate administrative reports, supporting more systematic enforcement on the roads.

Building on this experience, the government is now planning to expand the system by introducing an advanced AI-backed facial recognition feature. The upgraded system would use AI algorithms to analyze live camera footage, match facial data against authorized databases, and flag individuals potentially involved in criminal offenses in public places. The purpose of the AI enhancement is to lower crime rates and assist law enforcement in identifying suspects more efficiently in crowded urban environments.

Authorities emphasize that the AI system will function strictly as a decision-support tool. While the technology may detect patterns, generate alerts, and suggest potential matches, final decisions (including identity verification, investigation, and any legal action) will remain under the authority of human officers. The proposed expansion is presented as an AI-driven technological upgrade designed to strengthen public security while preserving human oversight in enforcement processes.

18. According to the information above, which road traffic monitoring system has been deployed in Kazakhstan?

- ☐ Qadam
- ☐ Bagyt
- ☐ National Traffic Coordination Platform
- ☐ Sergek

19. To what extent do you support the implementation of the AI-driven public security system? Rate from 1 to 10:

1	2	3	4	5	6	7	8	9	10
Strongly oppose					Strongly support				

20. How comfortable would you feel with the AI-driven system operating in public places? Rate from 1 to 10:

1	2	3	4	5	6	7	8	9	10
Very uncomfortable					Very comfortable				

BLOCK 8: DEBRIEF

Thank you for participating in this study!

Some of the information presented in this survey (including descriptions, statistics, and survey findings) was modified or constructed for research purposes. The materials you read should not be considered verified factual information. Any references to public opinion data, institutional actions, or survey results were included solely as part of the research design.

If you have any questions about the study or would like additional information about its purpose, please contact Amina Kosbayeva at amina.kosbayeva@nu.edu.kz

A.1.2. Questionnaire (Kazakh version)

**Мемлекетке деген сенім және мемлекеттік қызметтерде
ЖИ (жасанды интеллектті) пайдалануды қолдау****1 БЛОК: ДЕМОГРАФИЯЛЫҚ СҰРАҚТАР**

1. Сіздің жасыңыз?

- ☐ 18 – 24
- ☐ 25 – 34
- ☐ 35 – 44
- ☐ 45 – 54
- ☐ 55 – 64
- ☐ 65 немесе одан жоғары

2. Сіздің жынысыңыз?

- ☐ Әйел
- ☐ Еркек
- ☐ Басқа: _____
- ☐ Көрсетпеді жөн көремін

3. Сіз қазіргі уақытта Қазақстан азаматы / Қазақстанда тұруға ықтиярхаты бар азаматсыз ба?

- ☐ Иә
- ☐ Жоқ

4. Сіз өскен өңір?

- ☐ Қалалық жер
- ☐ Ауылдық жер

5. Қазіргі уақытта сіз қандай білім беру бағдарламасында оқисыз?

- ☐ Дайындық жылы
- ☐ Бакалавриат
- ☐ Магистратура
- ☐ Докторантура
- ☐ Басқа: _____

6. Қазіргі уақытта сіз қандай бағытта оқып жатырсыз?

- ☐ STEM бағыты (ғылым, технология, инженерия және математика)
- ☐ STEM емес (мысалы: әлеуметтік ғылымдар, гуманитарлық ғылымдар, бизнес, құқық, өнер және т. б.)
- ☐ Жауап беру қиын

2 БЛОК: САЯСИ МҮДДЕЛЕР

7. Сізді саясат қаншалықты қызықтырады? 1-ден 10-ға дейін бағалаңыз:

1	2	3	4	5	6	7	8	9	10
Мүлдем қызықтырмайды					Қатты қызықтырады				

8. Сіз жалпы мемлекетке қаншалықты сенесіз? 1-ден 10-ға дейін бағалаңыз:

1	2	3	4	5	6	7	8	9	10
Мүлдем сенбеймін					Толықтай сенемін				

3 БЛОК: ЖАСАНДЫ ИНТЕЛЛЕКТ

9. Сіз ЖИ (жасанды интеллект) технологияларымен қаншалықты таныссыз? 1-ден 10-ға дейін бағалаңыз:

1	2	3	4	5	6	7	8	9	10
Мүлдем таныс емеспін					Өте жақсы таныспын				

10. Сіз ЖИ (жасанды интеллекттің) қолдануына жалпы қалай қарайсыз? 1-ден 10-ға дейін бағалаңыз:

1	2	3	4	5	6	7	8	9	10
Өте нашар					Өте жағымды				

4 БЛОК: ВИНЬЕТКАЛАР

11. Келесі ақпаратты мұқият оқып шығыңыз:

Виньетка А: Құзыреттілік деңгейін манипуляциялау – 1 топ

Соңғы онжылдықта мемлекет күрделі реформаларды жүзеге асыруда және ірі мемлекеттік бағдарламаларды басқаруда жоғары әкімшілік және техникалық әлеуетті дәйекті түрде көрсетті. Негізгі ұлттық бастамалар министрліктер мен әкімдіктер (жергілікті әкімшілік) арасындағы орталықтандырылған үйлестіру кезінде нақты белгіленген стратегиялық жоспарларға сәйкес іске асырылады.

Мемлекеттік органдар мемлекеттік қызметтердің түрлі салаларындағы инфрақұрылымды сәтті жаңғыртып отыр. Цифрлық және әкімшілік жүйелер енгізілді, олар сұраныстарды өңдеу жылдамдығын, шешімдердің дәлдігін және ведомстволар арасындағы үйлестіруді арттырды. Мысалы, 2022 жылы азаматтар мен мемлекеттік органдар арасындағы өзара іс-қимылды жеңілдетуге арналған "e-Otinish" орталықтандырылған платформасы іске қосылды. Платформа арқылы азаматтар өтініштер бере алады, олардың қаралу барысын қадағалай алады, шағымдар жібере алады және мемлекеттік мекемелерге жеке бармай-ақ заңды рәсімдерге бастамашылық жасай алады. 2025 жылдың соңына қарай "e-Otinish" платформасы арқылы 5 миллионнан астам өтініш өңделді, олардың көпшілігіне (90%) қысқа мерзімде (бірнеше сағаттан 3 күнге дейін) жауаптар берілді.

Мемлекеттік қызметтерді ұсыну автоматтандырылған тексеру жүйелері мен стандартталған өтінімдерді өңдеу хаттамалары бар орталықтандырылған әкімшілік платформалардың арқасында жақсаруда. 2025 жылы "Deloitte" және "PwC" компаниялары жүргізген тәуелсіз аудиттердің деректері бойынша, бұл өтініштерді жылдам өңдеуді және рәсімдердің дәлдігінің жоғары деңгейін қамтамасыз етті.

Сонымен қатар мемлекеттік органдар сауда саласындағы ұлттық мақсаттарға тиімді қол жеткізуді қамтамасыз ете отырып, импорт пен экспортты басқаруда үйлестірудің жоғары деңгейін көрсетті. Жолға қойылған ведомствоаралық өзара іс-қимылдың, ресурстарды үнемді бөлудің және әкімшілік рәсімдерді уақтылы орындаудың арқасында тұрақты жұмыс қамтамасыз етілді. Нәтижесінде 2025 жылы жалпы тауар айналымы 150 миллиард долларға жетіп, соңғы 5 жылдағы көрсеткіштерден асып түсті.

Мемлекет соңғы онжылдықта мемлекеттік саясаттың бірінші кезекте азаматтардың әл-ауқатына, қадір-қасиетіне және ұзақ мерзімді қауіпсіздігіне бағытталуы керек екенін дәйекті түрде атап өтті. Ұлттық даму стратегияларында әлеуметтік қорғау, мүмкіндіктерге тең қол жеткізу және халықтың осал топтарын қолдау мемлекеттік саясаттың негізгі мақсаттары ретінде бірнеше рет белгіленген.

Азаматтардың пікірі мемлекеттік органдарға жетуі үшін бүкіл ел бойынша кері байланыс тетіктері ойластырылған. Қалаларда да, ауылдық жерлерде де қоғамдық форумдар мен кездесулер өткізіліп, онда тұрғындар өз мәселелер мен қажеттіліктерін ашық түрде бөлісіп келеді. Нәтижесінде мемлекет әлеуметтік қолдау бағдарламаларын түзетіп, халықтың осал топтарына жәрдемдесуге және жалпы қоғамның әл-ауқатын жақсартуға бағытталған жаңа бастамаларды жүзеге асырды. 2025 жылы "Pew Research Center" жүргізген сауалнамаға сәйкес, респонденттердің 78% "мемлекет мен сияқты адамдардың әл-ауқатына шын жүректен қамқорлық жасайды" деген пікірге келісті, ал 82% мемлекеттік саясат бірінші кезекте азаматтардың мүдделерін көрсетеді деп пайымдады.

Мемлекет Қазақстанның көптеген аймақтарына әсер еткен 2024 жылғы су тасқыны кезінде азаматтарға ерекше назар аударған. Қаржылық көмек пен құтқару жұмыстарын жүргізуден басқа, зардап шеккендер психологиялық көмек ала алатын жедел қолдау желілері ұйымдастырылды. Кейінгі қоғамдық сауалнамалар көрсеткендей, көптеген азаматтар бұл шараларды мемлекеттің дағдарыс кезінде азаматтардың әл-ауқатын қорғауға деген ұмтылысы іспеттес.

Виньетка С: Құзыреттілік пен тілектестік деңгейлерін манипуляциялау – 3 топ

Соңғы онжылдықта мемлекет азаматтардың әл-ауқатын қорғаудың маңыздылығын көрсете отырып, жоғары әкімшілік және техникалық әлеуетті арттырды. Министрліктер мен әкімдіктер (жергілікті әкімшіліктер) арасындағы үйлестіру кезінде нақты белгіленген стратегиялық жоспарларға сәйкес ірі реформалар жүзеге асырылды.

Мемлекеттің бастамалары қиын өмірлік жағдайдағы отбасыларға, ауыл тұрғындарына және табысы төмен адамдарға атаулы көмек бағдарламаларын кеңейтуге бағытталған. Көмекке ең мұқтаж адамдарға жетуі үшін әлеуметтік қолдау тетіктері күшейтілді. Тұрақты қоғамдық есеп беру, сонымен қатар ашықтық пен есеп беруді арттыруға бағытталған. Нәтижесінде, 2025 жылдың соңына қарай кедейлік шегінен төмен өмір сүретін адамдардың үлесі 5,1% - дан 1% - ға дейін қысқарды.

Дағдарыс кезеңінде мемлекет, сонымен қатар азаматтарды экономикалық және әлеуметтік тәуекелдерден қорғауға, үй шаруашылықтары мен шағын бизнеске қаржылық жүктемені азайту үшін, қолдау шараларын енгізуге міндеттеме алды. Мәселен, 2024 жылғы су тасқынынан кейін бірнеше аймақтарда бюрократиялық кідіріссіз зардап шеккен халыққа қаржылық көмек көрсетілді. Осының арқасында азаматтар төлемдерді оқиғадан бірнеше күн өткен соң алу мүмкіндігіне қол жеткізді.

Сонымен қатар, қоғамдық тыңдаулар мен кері байланыс тетіктері ұйымдастырылып, адамдар өздерінің мәселелері мен ұсыныстары туралы ашық айтты. Су тасқыны кезінде және одан кейін азаматтардың уәждерін қысқа мерзімде (бірнеше сағаттан 3 күнге дейін) шешу үшін тікелей байланыс желілері ашылды.

Виньетка D: Манипуляциялар жоқ – 4 топ

Қысқы Олимпиада ойындары - бұл әлемнің түкпір-түкпірінен келген спортшыларды әртүрлі пәндер бойынша жарыстарға біріктіретін ірі халықаралық спорттық іс-шара. 2026 жылы Қысқы Олимпиада Италияның Милан және Кортина Д'Ампеццо альпілік курорттық қалаларында өтті. Жарыс бағдарламасына шайбалы хоккей, мәнерлеп сырғанау, биатлон, бобслей, тау шаңғысы, шаңғы жарысы, фристайл, сноуборд, шорт-трек, керлинг, шана спорты, шаңғы қоссайысы, қаңқа, шаңғы тебу және шаңғымен секіру сияқты спорт түрлері кірді.

2026 жылғы ойындарға 93 елдің өкілдері қатысып, қатысушылар саны бойынша ең көп Еуропа, Америка және Азия делегацияларынан құралған. Медальдардың басым көпшілігі Норвегия, АҚШ, Нидерланды, Италия және Германия мемлекеттерінің еншісінде. Олимпиадада Оңтүстік Америка аймағынан Бразилия алғашқы болып медальді қанжығасына байлады.

2026 жылғы ойындардың ең ересек медалінің иегері әйелдер керлинг спорт түрінен күміс медальді жеңіп алған Швейцариялық 46 жасар Сильвана Тиринзони болса, сноубордта әйелдер жартылай құбырында алтын жеңіп алған ең жас медаль иегері Корея Республикасының 17 жасар Чой Гаон биіктен көрінді. Бұл ойындар тарихтағы ең гендерлік теңдестірілген Қысқы Олимпиада ойындары деп аталып, әйелдер барлық спортшылардың 47% құрады.

5 БЛОК: ЗЕЙІНДІ ТЕКСЕРУ

12 (А). Жоғарыда келтірілген ақпаратқа сәйкес, 2025 жылы қандай әлемдік компаниялар әкімшілік платформаларға аудит жүргізді? (бұл сұраққа тек 1 топтағы респонденттер жауап береді)

- ☐ KPMG және EY
- ☐ McKinsey және BCG
- ☐ Deloitte және PwC
- ☐ BDO және RSM

12 (В). Жоғарыда келтірілген ақпаратқа сәйкес, 2025 жылы Қазақстанда қандай халықаралық ұйым қоғамдық пікірге сауалнама жүргізді? (бұл сұраққа тек 2 топтағы респонденттер жауап береді)

- ☐ Pew Research Center
- ☐ Gallup World Poll
- ☐ World Values Survey
- ☐ Ipsos

12 (С). Жоғарыда келтірілген ақпаратқа сәйкес, 2024 жылғы су тасқыны кезінде адамдардың проблемалары қаншалықты тез шешілді? (бұл сұраққа тек 3 топтағы респонденттер жауап береді)

- ☐ Бірнеше минут ішінде
- ☐ Бірнеше сағаттан 3 күнге дейін
- ☐ Бірнеше ай ішінде
- ☐ Жоғарыда айтылғандардың ешқайсысы жоқ

12 (D). Жоғарыда келтірілген ақпаратқа сәйкес, 2026 жылғы қысқы Олимпиада ойындарына қанша ел қатысты? (бұл сұраққа тек 4 топтағы респонденттер жауап береді)

- ☐ 84 ел
- ☐ 93 ел
- ☐ 155 ел
- ☐ 77 ел

6 БЛОК: МАНИПУЛЯЦИЯНЫ ТЕКСЕРУ

13. Сіздің ойыңызша, мемлекет біздің еліміздегі мәселелерді шешуде қаншалықты тиімді? 1-ден 10-ға дейін бағалаңыз:

1	2	3	4	5	6	7	8	9	10
Мүлдем тиімсіз									Өте тиімді

14. Реформалар мен жалпы саясатты іске асыру бойынша мемлекеттің техникалық және әкімшілік әлеуетін қалай бағалайсыз? 1-ден 10-ға дейін бағалаңыз:

1	2	3	4	5	6	7	8	9	10
Өте төмен									Өте жоғары

15. Мемлекет адамдардың әл-ауқатына қаншалықты мән береді деп ойлайсыз? 1-ден 10-ға дейін бағалаңыз:

1	2	3	4	5	6	7	8	9	10
Мүлдем мән бермейді									Өте қамқор

16. Мемлекет азаматтардың мүддесі үшін әрекет етуге қаншалықты ұмтылады деп ойлайсыз? 1-ден 10-ға дейін бағалаңыз:

1	2	3	4	5	6	7	8	9	10
Мүлдем ұмтылмайды									Өте ұмтылады

7 БЛОК: МЕМЛЕКЕТТІК ҚЫЗМЕТТЕРДЕГІ ЖИ

17. Төмендегі ақпаратты мұқият оқып, сұрақтарға жауап беріңіз:

Соңғы жылдары Қазақстанда қоғамдық қауіпсіздікті арттыру және жол қозғалысын басқару үшін мониторингтің цифрлық технологиялары енгізілуде. Мысалы, ірі қалаларда жол қозғалысын бақылау және жылдамдықты арттыру немесе қызыл жарыққа өту сияқты бұзушылықтарды анықтау үшін қолданылатын "Sergek" жүйесі. Жүйе жол қозғалысы ережелерінің бұзылуын автоматты түрде анықтау және әкімшілік материалдарды қалыптастыру үшін жасанды интеллектке негізделген бейне аналитиканы пайдаланады, бұл жол ережелерінің сақталуын жүйелі түрде бақылауға көмектеседі.

Осы тәжірибеге сүйене отырып, мемлекет жасанды интеллект негізінде бетті танудың қосымша функциясын енгізу арқылы жүйені кеңейтуді жоспарлап отыр. Жаңартылған жүйе бейнебақылау камераларындағы суреттерді талдайды, деректерді ашық дерекқорлармен салыстырады, сондай-ақ қоғамдық орындардағы қылмыстарға қатысы бар адамдарды анықтайды. Мұндай кеңейтудің мақсаты - қылмыс деңгейін төмендету және құқық қорғау органдарына халық тығыз орналасқан қалалардағы күдіктілерді тезірек анықтауға көмектесу.

Мемлекет жасанды интеллект жүйесі, тек шешім қабылдауды қолдау құралы ретінде жұмыс істейтінін атап көрсетеді. Бұл технология жүйелік заңдылықтарды анықтай алады, хабарламалар жасай алады және ықтимал сәйкестіктерді белгілей алады, бірақ, соңғы шешімдерді (сонымен қатар жеке басын тексеру, тергеу және кез келген заңды әрекеттерді) құқық қорғау органдарының қызметкерлері қабылдайды.

Жүйені кеңейтуді мемлекет құқық қолдану процестеріне адамның бақылауын сақтай отырып, қоғамдық қауіпсіздікті арттыруға бағытталған технологиялық жаңарту ретінде ұсынады.

18. Жоғарыда келтірілген ақпаратқа сәйкес, Қазақстанда жол қозғалысы мониторингінің қандай жүйесі енгізілді?

- ☐ Qadam
☐ Bagyt
☐ Жол қозғалысын үйлестірудің ұлттық платформасы
☐ Sergek

19. Сіз жасанды интеллектке негізделген қоғамдық қауіпсіздік жүйесін енгізуді қаншалықты қолдайсыз? 1-ден 10-ға дейін бағалаңыз:

1	2	3	4	5	6	7	8	9	10
Толықтай қолдаймын					Мүлдем қолдамаймын				

20. Егер жасанды интеллектке негізделген қауіпсіздік жүйесі қоғамдық орындарда қолданылса, Сіз өзіңізді қаншалықты жайлы сезінер едіңіз? 1-ден 10-ға дейін бағалаңыз:

1	2	3	4	5	6	7	8	9	10
Мүлдем жайсыз					Өте жайлы				

8 БЛОК: ЕСКЕРТПЕ

Зерттеуге қатысқаныңыз үшін рахмет!

Осы сауалнамада берілген кейбір ақпарат (сипаттамаларды, статистиканы және сауалнама нәтижелерін қоса) зерттеу мақсатында өзгертілді немесе қосылды. Берілген деректерді нақты немесе сенімді ақпарат ретінде қабылдауға болмайды.

Егер, Сізде зерттеуге қатысты сұрақтарыңыз болса немесе оның мақсаттары туралы қосымша ақпарат алғыңыз келсе, Амина Косбаеваға электронды пошта арқылы хабарласыңыз: amina.kosbayeva@nu.edu.kz

A.1.3. Questionnaire (Russian version)

Доверие к государству и поддержка использования ИИ (искусственного интеллекта) в государственных услугах**БЛОК 1: ДЕМОГРАФИЧЕСКИЕ ВОПРОСЫ**

1. Сколько вам лет?

- ☐ 18 – 24
- ☐ 25 – 34
- ☐ 35 – 44
- ☐ 45 – 54
- ☐ 55 – 64
- ☐ 65 или старше

2. Ваш пол?

- ☐ Женский
- ☐ Мужской
- ☐ Другое: ____
- ☐ Предпочитаю не указывать

3. Являетесь ли вы в настоящее время гражданином / имеющим вид на жительство Казахстана?

- ☐ Да
- ☐ Нет

4. В каком типе местности вы выросли?

- ☐ Городская местность
- ☐ Сельская местность

5. На какой образовательной программе вы в данный момент обучаетесь?

- ☐ Подготовительный год
- ☐ Бакалавриат
- ☐ Магистратура
- ☐ Докторантура
- ☐ Другое: ____

6. По какому направлению вы в данный момент обучаетесь?

- ☐ STEM (естественные науки, технологии, инженерия, математика)

- ☐ Не-STEM (социальные науки, гуманитарные науки, бизнес, право, искусство и т.д.)
- ☐ Затрудняюсь ответить

БЛОК 2: ПОЛИТИЧЕСКИЕ ИНТЕРЕСЫ

7. Насколько вы интересуетесь политикой? Оцените от 1 до 10:

1	2	3	4	5	6	7	8	9	10
Совсем не интересуюсь									Очень интересуюсь

8. Насколько в целом вы доверяете государству? Оцените от 1 до 10:

1	2	3	4	5	6	7	8	9	10
Совсем не доверяю									Полностью доверяю

БЛОК 3: ИСКУССТВЕННЫЙ ИНТЕЛЛЕКТ

9. Насколько хорошо вы знакомы с технологиями ИИ (искусственного интеллекта)? Оцените от 1 до 10:

1	2	3	4	5	6	7	8	9	10
Совсем не знаком (-а)									Очень хорошо знаком (-а)

10. Как вы в целом относитесь к использованию ИИ (искусственного интеллекта)? Оцените от 1 до 10:

1	2	3	4	5	6	7	8	9	10
Очень негативн о									Очень позитивн о

БЛОК 4: ВИНЬЕТКИ

11. Пожалуйста, внимательно прочтите следующую информацию:

Виньетка А: Манипулирование уровнем компетенций – Группа 1

За последнее десятилетие государство последовательно демонстрировало высокий административный и технический потенциал в реализации сложных реформ и управлении крупными государственными проектами. Ключевые национальные инициативы реализовывались в соответствии с четко определенными стратегическими планами при централизованной координации между министерствами и акиматами (местной администрацией).

Государственные органы успешно модернизировали инфраструктуру в различных сферах государственных услуг. Были внедрены цифровые и административные системы, которые повысили скорость обработки запросов, точность решений и координацию между ведомствами. К примеру, в 2022 году была запущена централизованная платформа «e-Otinish», предназначенная для упрощения взаимодействия между гражданами и государственными органами. Через платформу граждане могут подавать обращения, отслеживать ход их рассмотрения, направлять жалобы и инициировать юридические процедуры без личного посещения государственных учреждений. К концу 2025 года через платформу «e-Otinish» было обработано более 5 миллионов обращений, при этом на большинство из них (90%) были даны ответы в короткие сроки (от нескольких часов до 3 дней).

Предоставление государственных услуг также улучшается благодаря централизованным административным платформам с автоматизированными системами проверки и стандартизированными протоколами обработки заявок. По данным независимых аудитов, проведенных в 2025 году компаниями «Deloitte» и «PwC», это обеспечило более быструю обработку обращений и высокий уровень точности процедур.

Государственные органы также продемонстрировали высокий уровень координации в управлении импортом и экспортом, обеспечив эффективное достижение национальных целей в сфере торговли. Благодаря налаженному межведомственному взаимодействию, рентабельному распределению ресурсов и своевременному выполнению административных процедур была обеспечена стабильная работа. В результате чего общий товарооборот в 2025 году достиг 150 миллиардов долларов, превысив показатели последних 5 лет.

За последнее десятилетие государство последовательно подчеркивало, что государственная политика должна в первую очередь быть направлена на благополучие, достоинство и долгосрочную безопасность граждан. В национальных стратегиях развития социальная защита, равный доступ к возможностям и поддержка уязвимых групп населения неоднократно обозначались как ключевые цели государственной политики.

Для того, чтобы мнение граждан доходило до государственных органов, по всей стране были созданы механизмы обратной связи. Как в городах, так и в сельской местности проводились общественные форумы и встречи, на которых жители могли открыто делиться своими проблемами и потребностями. В результате правительство корректировало программы социальной поддержки и запускало новые инициативы, направленные на помощь уязвимым группам населения и улучшение благополучия общества в целом. Согласно опросу общественного мнения, проведенному «Pew Research Center» в 2025 году, 78% респондентов согласились с утверждением, что «государство искренне заботится о благополучии таких людей, как я», а 82% заявили, что считают, что государственная политика в первую очередь отражает интересы граждан.

Особое внимание государство проявило к гражданам во время паводков 2024 года, затронувших большинство регионов Казахстана. Помимо финансовой помощи и проведения спасательных операций, были организованы горячие линии поддержки, через которые пострадавшие могли получить психологическую помощь. Последующие общественные опросы показали, что многие граждане восприняли эти меры как свидетельство стремления государства защитить благополучие граждан в период кризиса.

Виньетка С: Манипулирование уровнями компетенций и благожелательности –
Группа 3

За последнее десятилетие государство последовательно демонстрировало высокий административный и технический потенциал, одновременно подчеркивая важность защиты благополучия граждан. Крупные реформы были реализованы в соответствии с четко определенными стратегическими планами при координации между министерствами и акиматами (местными администрациями).

Инициативы государства были направлены на расширение программ адресной помощи семьям в трудной жизненной ситуации, сельским жителям и лицам с низкими доходами. Были усилены механизмы социальной поддержки, чтобы помощь доходила до наиболее нуждающихся. Регулярная публичная отчетность также была направлена на повышение прозрачности и подотчетности. В результате к концу 2025 года доля людей, живущих за чертой бедности, сократилась с 5,1% до 1%.

В периоды кризиса власти также заявляли о своей приверженности защите граждан от экономических и социальных рисков, вводя меры поддержки для снижения финансовой нагрузки на домохозяйства и малый бизнес. Например, после паводков 2024 года в нескольких регионах были запущены ускоренные процедуры предоставления финансовой помощи пострадавшему населению без бюрократических задержек. Благодаря этому, люди могли получить выплаты уже через несколько дней после происшествия.

Помимо этого были организованы общественные слушания и механизмы обратной связи, на которых люди могли открыто рассказать о своих проблемах и предложениях. Во время и после паводков были открыты прямые линии связи, через которые люди могли решить свои вопросы в очень короткие сроки (от нескольких часов до 3 дней).

Виньетка D: Нет манипуляций – Группа 4

Зимние Олимпийские игры - это крупное международное спортивное событие, которое объединяет спортсменов со всего мира для соревнований в различных дисциплинах. В 2026 году Зимние Олимпийские игры проходили в Милане и альпийском курортном городе Кортина-д'Ампеццо в Италии. В программу соревнований входили такие виды спорта как хоккей с шайбой, фигурное катание, биатлон, бобслей, горнолыжный спорт, лыжные гонки, фристайл, сноуборд, шорт-трек, керлинг, санный спорт, лыжное двоеборье, скелетон, ски-альпинизм и прыжки на лыжах с трамплина.

В Играх 2026 года участие приняли представители 93 стран. Самыми многочисленными по количеству участников были делегации из Европы, Америки и Азии. Норвегия, США, Нидерланды, Италия и Германия завоевали наибольшее количество медалей. Бразилия стала первой страной Южной Америки, завоевавшей олимпийскую медаль.

Самой взрослой медалисткой Игр 2026 года стала 46-летняя Сильвана Тиригони из Швейцарии, завоевавшая серебряную медаль в женском керлинге. Самым юным медалистом стала представительница Республики Корея – 17-летняя Чхве Гаон, выигравшая золото в женском хафпайпе на сноуборде. Эти игры также были названы самыми гендерно сбалансированными зимними Олимпийскими играми в истории: женщины составили 47% всех спортсменов.

БЛОК 5: ПРОВЕРКА ВНИМАТЕЛЬНОСТИ

12 (А). Согласно приведенной выше информации, какие мировые компании провели аудиты административных платформ в 2025 году? (на этот вопрос отвечают только респонденты из группы 1)

- ☐ KPMG и EY
- ☐ McKinsey и BCG
- ☐ Deloitte и PwC
- ☐ BDO и RSM

12 (В). Согласно приведенной выше информации, какая международная организация провела опрос общественного мнения в Казахстане в 2025 году? (на этот вопрос отвечают только респонденты из группы 2)

- ☐ Pew Research Center
- ☐ Gallup World Poll
- ☐ World Values Survey
- ☐ Ipsos

12 (С). Согласно приведенной выше информации, насколько быстро были решены проблемы людей во время и после паводков 2024 года? (на этот вопрос отвечают только респонденты из группы 3)

- ☐ За несколько минут
- ☐ От нескольких часов до 3 дней
- ☐ За несколько месяцев
- ☐ Ничего из вышеперечисленного

12 (D). Согласно приведенной выше информации, сколько стран приняли участие в зимних Олимпийских играх 2026 года? (на этот вопрос отвечают только респонденты из группы 4)

- ☐ 84 страны
- ☐ 93 страны
- ☐ 155 стран
- ☐ 77 стран

БЛОК 6: ПРОВЕРКА МАНИПУЛЯЦИИ

13. Насколько эффективно, по вашему мнению, государство решает проблемы в нашей стране? Оцените от 1 до 10:

1	2	3	4	5	6	7	8	9	10
Совсем неэффективно									Очень эффективно

14. Как бы вы оценили технический и административный потенциал государства по реализации реформ и политики в целом? Оцените от 1 до 10:

1	2	3	4	5	6	7	8	9	10
Очень низкий									Очень высокий

15. Как вы считаете, насколько государство заботится о благополучии людей? Оцените от 1 до 10:

1	2	3	4	5	6	7	8	9	10
Совсем не заботится									Очень заботится

16. Как вы считаете, насколько государство стремится действовать в интересах граждан? Оцените от 1 до 10:

1	2	3	4	5	6	7	8	9	10
Совсем не стремится									Очень стремится

БЛОК 7: ИИ В ГОСУДАРСТВЕННЫХ УСЛУГАХ

17. Пожалуйста, внимательно прочтите следующую информацию и ответьте на вопросы, приведенные ниже:

В последние годы в Казахстане внедряются цифровые технологии мониторинга для повышения общественной безопасности и управления дорожным движением. Одним из примеров является система «Sergek», которая используется в крупных городах для наблюдения за дорожным движением и выявления нарушений таких как превышение скорости или проезд на красный свет. Система использует видеоаналитику на базе искусственного интеллекта для автоматического обнаружения нарушений правил дорожного движения и формирования административных материалов, что помогает более системно контролировать соблюдение правил на дорогах.

Опираясь на этот опыт, государство планирует расширить систему, внедрив дополнительную функцию распознавания лиц на основе искусственного интеллекта.

Обновленная система будет анализировать изображения с камер видеонаблюдения, сопоставлять данные с открытыми базами данных, а также выявлять людей, возможно причастных к преступлениям в общественных местах. Цель такого расширения - снизить уровень преступности и помочь правоохранительным органам быстрее выявлять подозреваемых в густонаселенных городах.

Государство подчеркивает, что система искусственного интеллекта будет функционировать исключительно как инструмент поддержки принятия решений. Эта технология может выявлять закономерности, генерировать уведомления и обозначать возможные совпадения, однако окончательные решения (а также проверка личности, расследование и любые юридические действия) будут приниматься сотрудниками правоохранительных органов.

Расширение системы представлено государством как технологическое обновление, направленное на повышение общественной безопасности при сохранении человеческого контроля над процессами правоприменения.

18. Согласно приведенной выше информации, какая система мониторинга дорожного движения была внедрена в Казахстане?

- ☐ Qadam
- ☐ Bagyt
- ☐ Национальная платформа координации дорожного движения
- ☐ Sergek

19. В какой степени вы поддерживаете внедрение системы общественной безопасности, основанной на искусственном интеллекте? Оцените от 1 до 10:

1	2	3	4	5	6	7	8	9	10
Полностью не поддерживаю									Полностью поддерживаю

20. Насколько комфортно вы бы себя чувствовали, если бы система безопасности на основе искусственного интеллекта использовалась в общественных местах? Оцените от 1 до 10:

1	2	3	4	5	6	7	8	9	10
Совсем некомфортно									Очень комфортно

БЛОК 8: ПРИМЕЧАНИЕ

Благодарим вас за участие в этом исследовании!

Некоторая информация, представленная в этом опросе (включая описания, статистические данные и результаты опросов), была изменена или добавлена в

исследовательских целях. Приведенные данные не следует воспринимать как фактическую или достоверную информацию.

Если у вас возникнут какие-либо вопросы по поводу исследования или вы хотите получить дополнительную информацию о его целях, пожалуйста, свяжитесь с Аминой Косбаевой по эл. почте: amina.kosbayeva@nu.edu.kz

A.2.1. Consent form (English version)

You are invited to participate in a research study examining public attitudes toward the government policies.

If you agree to participate in this study, you will be asked to read short informational text, answer several questions about your opinion and perception, as well as providing basic demographic data. The survey will take approximately 15 – 20 minutes.

This study is minimal risk. No sensitive personal information will be collected.

While there are no direct personal benefit, your responses will contribute to academic research on public attitudes toward the government policies.

No tangible compensation will be provided for participation. The results of the study will be available upon completion as part of a master's thesis, which will be uploaded to the university's official library repository.

Any information that is obtained during this study will be kept confidential to the full extent possible.

Participation in this study is strictly voluntary, and if agreement to participation is given, it can be withdrawn at any time without prejudice.

It is understood that should any questions or comments arise regarding this project, or a research related injury is received, the Principal Investigator, Amina Kosbayeva, amina.kosbayeva@nu.edu.kz should be contacted. Any other questions or concerns may be addressed to the Nazarbayev University SSH IREC, sshirec@nu.edu.kz.

By clicking "I agree" below you are indicating that you are at least 18 years old, have read and understood this consent form and agree to participate in this research study:

- ☐ I Agree
- ☐ I Disagree

A.2.2. Consent form (Kazakh version)

Сізді, үкіметтің саясатына қоғамның көзқарасын анықтайтын зерттеуге қатысуға шақырамын.

Егер, Сіз осы зерттеуге қатысуға келіссеңіз, сізден қысқаша ақпараттық мәтінді оқып, пікіріңіз бен қабылдауыңыз туралы бірнеше сұрақтарға жауап беру және негізгі демографиялық мәліметтерді ұсыну сұралады. Сауалнама шамамен 15-20 минутты қажет етеді.

Бұл зерттеуде минималды қауіп бар. Құпия жеке ақпарат жиналмайды.

Тікелей жеке пайда болмаса да, сіздің жауаптарыңыз үкіметтің саясатына қоғамның көзқарасын ғылыми зерттеуге ықпал етеді.

Қатысу үшін айтарлықтай өтемақы төленбейді. Зерттеу нәтижелері университеттің ресми кітапхана қоймасына жүктелетін магистрлік диссертацияның бөлігі ретінде аяқталғаннан кейін қол жетімді болады.

Осы зерттеу барысында алынған кез келген ақпарат мүмкіндігінше құпия сақталады.

Бұл зерттеуге қатысу ерікті болып табылады және қатысуға келісім алған жағдайда, Сіз келісімді кері қайтаруға құқылысыз.

Осы жобаға қатысты қандай да бір сұрақтар, түсініктемелер туындаған немесе зерттеулерге байланысты жарақат алған жағдайда бас зерттеуші Амина Қосбаевамен байланысу керек (amina.kosbayeva@nu.edu.kz). Кез келген басқа сұрақтармен немесе алаңдаушылықтармен Назарбаев Университетінің Жаратылыстану, әлеуметтік және гуманитарлық ғылымдар мектебінің Ғылыми зерттеулер этикасы комитетіне хабарласуға болады (sshirec@nu.edu.kz).

Төмендегі "Мен келісемін" түймесін басу арқылы Сіз кем дегенде 18 жаста екеніңізді растайсыз, осы келісім формасын оқып, түсінесіз және осы ғылыми зерттеуге қатысуға келісесіз:

- ☐ Мен келісемін
- ☐ Мен келіспеймін

A.2.3. Consent from (Russian version)

Вас приглашают принять участие в исследовании, посвященном изучению отношения общественности к государственной политике.

Если вы согласитесь принять участие в этом исследовании, вам будет предложено прочитать краткую информацию, ответить на несколько вопросов о вашем мнении и восприятии, а также предоставить некоторые демографические данные. Опрос займет около 15-20 минут.

Это исследование сопряжено с минимальным риском. Конфиденциальная личная информация собираться не будет.

Несмотря на отсутствие прямой личной выгоды, ваши ответы будут способствовать научному исследованию отношения общественности к государственной политике.

За участие не будет выплачиваться какая-либо компенсация. Результаты исследования будут доступны по завершении как часть магистерской диссертации, которая будет загружена в официальное библиотечное хранилище университета.

Любая информация, полученная в ходе этого исследования, будет сохранена в тайне в максимально возможной степени.

Участие в данном исследовании является строго добровольным, и, в случае получения согласия на участие, оно может быть отозвано в любое время.

В случае возникновения каких-либо вопросов или комментариев относительно данного проекта, или получения травмы, связанной с исследованием, следует связаться с главным исследователем, Аминой Косбаевой, amina.kosbayeva@nu.edu.kz. По любым другим вопросам можно обращаться в Комитет по этике научных исследований Школы естественных, социальных и гуманитарных наук Назарбаев Университета, sshirec@nu.edu.kz.

Выбрав "Я согласен" ниже, вы подтверждаете, что вам исполнилось не менее 18 лет, вы прочитали и поняли данную форму согласия и согласны участвовать в данном научном исследовании:

- ☐ Я согласен

☐ Я не согласен

A.3. Email invitation to participate in the study

Table A1

Dear Students,

My name is [PI's name]¹. I am a second year MAPSIR program student at NU.

I am inviting you to participate in a **research study conducted as a part of my master's thesis**. This study explores public attitudes toward government policies.

- Participation involves completing a **short online survey** that takes approximately 5 – 10 minutes.
- Participation is entirely **voluntary, anonymous**, and **you may choose to stop the survey at any time**.

If you would like to participate, please follow any of the links below (please, choose the language you are most comfortable with):

English version: https://nukz.qualtrics.com/jfe/form/SV_aXW5XfabMd5YzMq

Kazakh version: https://nukz.qualtrics.com/jfe/form/SV_5sUCzGydqd4zun4

Russian version: https://nukz.qualtrics.com/jfe/form/SV_0SutY173fCqRr0

If you have any questions about the study, please contact [PI's name] at [PI's email address] or the Primary Advisor at [PA's email address]².

Thank you for your interest and time!

Note: This study has been approved by the NU SSH IREC and the Political Science and International Relations department.

Құрметті студенттер,

Менің есімім [PI's name]. Мен НУ-дағы MAPSIR бағдарламасының екінші курс студентімін.

Мен сіздерді **магистрлік диссертациям аясында жүргізілген зерттеуге** қатысуға шақырамын. Бұл жұмыс қоғамның мемлекеттік саясатқа қатынасын зерттейді.

- Қатысу шамамен 5-10 минутты алатын **қысқа онлайн сауалнаманы** толтыруды қамтиды.
- Қатысу толығымен **ерікті және жасырын** болып табылады. Сіз **кез келген уақытта сауалнамаға қатысуды тоқтата аласыз**.

Егер сіз қатысқыңыз келсе, төмендегі сілтемелердің кез-келгеніне өтіңіз (сізге ыңғайлы тілді таңдаңыз):

Ағылшын нұсқасы:

https://nukz.qualtrics.com/jfe/form/SV_aXW5XfabMd5YzMq

Қазақша нұсқасы: https://nukz.qualtrics.com/jfe/form/SV_5sUCzGydqd4zun4

Орысша нұсқасы: https://nukz.qualtrics.com/jfe/form/SV_0SutY173fCqRr0

Егер сізде зерттеуге қатысты сұрақтарыңыз болса, [PI's name] [PI's email address] электрондық пошта арқылы хабарлассаңыз болады. Немесе [PA's name] бас ғылыми жетекшісімен [PA's email address] электрондық пошта арқылы хабарлассаңыз болады. Қызығушылық пен уақыт бөлгеніңіз үшін рахмет!

Ескерту: бұл зерттеуді Назарбаев Университетінің Жаратылыстану, әлеуметтік және гуманитарлық ғылымдар мектебінің Ғылыми зерттеулер этикасы комитеті және Саясаттану және халықаралық қатынастар департаменті мақұлдады.

¹ PI - Principal Investigator

² PA - Primary Advisor

Уважаемые студенты,

Меня зовут [PI's name]. Я студентка второго курса программы MAPSIR в НУ.

Я приглашаю вас принять участие в **исследовании, проводимом в рамках моей магистерской диссертации**. В этой работе исследуется отношение общественности к государственной политике.

- Участие предполагает заполнение **короткого онлайн-опроса**, который занимает примерно 5-10 минут.
- Участие является полностью **добровольным** и **анонимным**. Вы можете в **любой момент прекратить участие в опросе**.

Если вы хотите принять участие, пожалуйста, перейдите по любой из приведенных ниже ссылок (пожалуйста, выберите наиболее удобный для вас язык):

Английская версия:

https://nukz.qualtrics.com/jfe/form/SV_aXW5XfabMd5YzMq

Казахская версия: https://nukz.qualtrics.com/jfe/form/SV_5sUCzGydqd4zun4

Русская версия: https://nukz.qualtrics.com/jfe/form/SV_0SutY173fCqtRr0

Если у вас есть какие-либо вопросы по поводу исследования, пожалуйста, свяжитесь с [PI's name] по email-адресу [PI's email address] или с главным научным руководителем [PA's name] по email-адресу [PA's email address].

Спасибо вам за проявленный интерес и уделенное время!

Примечание: Это исследование было одобрено Комитетом по этике научных исследований Школы естественных, социальных и гуманитарных наук Назарбаев Университета и департаментом Политологии и Международных отношений.

Appendix B. Results

B.1.1. Descriptive statistics

Table B1 (full sample)

Variable	Obs.	Mean	SD	Median	Min.	Max.
Interest in politics	210	6.34	2.58	7.0	1	10
Trust in government	210	4.29	1.98	4.0	1	10
Familiarity with AI	210	7.27	1.78	7.0	1	10
Attitude toward AI	210	6.37	2.24	7.0	1	10
Competence	210	5.06	1.81	5.0	1	9
Benevolence	210	4.62	2.09	4.5	1	10
Support for AI	210	5.90	2.52	6.5	1	10

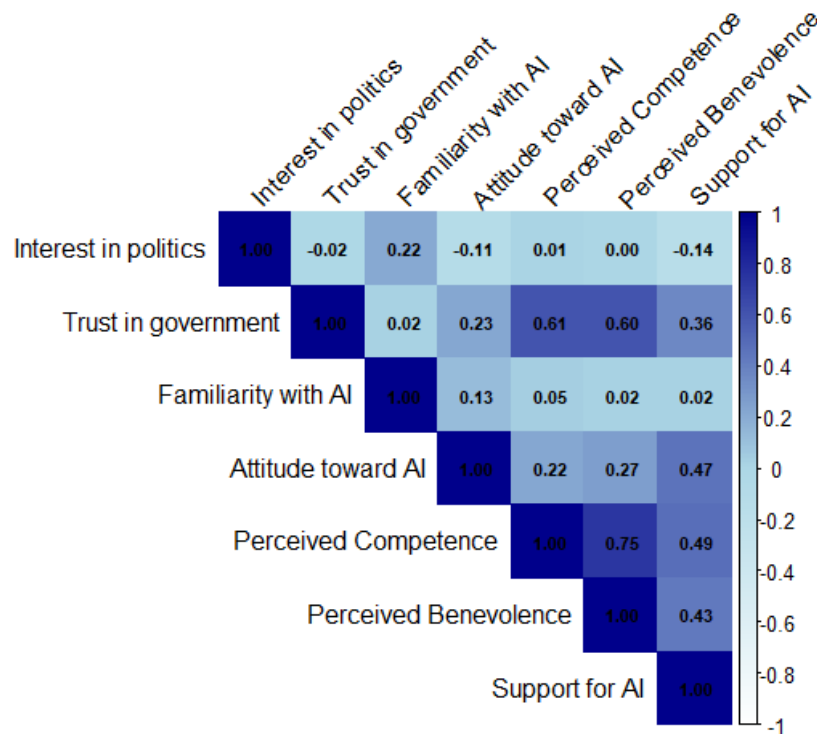
Table B2 (filtered sample)

Variable	Obs.	Mean	SD	Median	Min.	Max.
Interest in politics	163	6.34	2.55	7.0	1	10
Trust in government	163	4.29	2.03	4.0	1	10
Familiarity with AI	163	7.37	1.73	7.0	4	10
Attitude toward AI	163	6.21	2.27	7.0	1	10
Competence	163	5.11	1.83	5.5	1	9
Benevolence	163	4.62	2.15	4.5	1	10
Support for AI	163	5.85	2.63	6.0	1	10

B.1.2. Correlation matrix

The correlation matrix provides insights into the relationships between key variables and offers preliminary assessment of the theoretical expectations prior to regression analysis. Both dimensions of trust in government - perceived competence and benevolence - are found to be positively correlated with support for AI in the public sector (0.49 and 0.43 consequently). These relationships are consistent with the expectations outlined in Hypothesis 1 and 2, suggesting that individuals who evaluate the government as more capable and more well-intentioned would be more likely to support the use of AI in public services.

Figure B1: Correlation matrix



Perceived competence and benevolence themselves are highly correlated (0.75), which might indicate that respondents who view the government as technically and administratively capable also tend to perceive it as acting in public interest. While this finding aligns with the existing literature on multidimensional trust in government, the strength of the relationship might raise questions regarding the conceptual overlap between the two variables. The inclusion of both of these independent variables with an interaction term in the regression

model has been done to assess the independent and conditional effects, thus mitigating the above mentioned concern.

Baseline general trust in government is strongly correlated with both the perceived competence and benevolence, confirming that the experimental setting is fit to carry out the relevant evaluations. Moreover, trust in government is found to be moderately correlated with the support for AI (0.36) which reinforces the central argument that attitudes toward governmental institutions shape the acceptance of AI tools in the public sector.

Attitudes towards AI are also positively correlated with the support for AI in public services, thus general susceptibility to algorithm-driven technology plays an important role in influencing the acceptance of such technology in governance. Familiarity with AI, on the other hand, is more weakly correlated with the dependent variable, which suggests that exposure to AI doesn't necessarily lead to its support in public services.

B.1.3. Balance charts

Table B3 (full sample)

		Group A	Group B	Group C	Group D
Interest in politics		6 (2.67)	6.24 (2.68)	6.94 (2.38)	6.15 (2.56)
Trust in government		4.25 (1.84)	4.02 (1.95)	4.8 (1.86)	4.06 (2.22)
Familiarity with AI		7.08 (1.55)	7.36 (2.13)	7.41 (1.75)	7.25 (1.69)
Attitude toward AI		6.15 (1.97)	6.94 (2.35)	6.63 (2.14)	5.77 (2.37)
Gender	Male	45.3%	42%	42.6%	54.7%
	Female	54.7%	56%	57.4%	45.3%
	Prefer not to say	0%	2%	0%	0%
Age	18–24	60.4%	56%	55.6%	67.9%
	25–34	34%	32%	29.6%	22.6%
	35–44	5.7%	12%	13%	9.4%
	45–54	0%	0%	1.9%	0%
Field of study	Non-STEM	47.2%	48%	59.3%	41.5%
	STEM	49.1%	50%	37%	54.7%
	Not sure	3.8%	2%	3.7%	3.8%
Academic program	Foundation Year	1.9%	0%	0%	0%
	Bachelor's	35.8%	44%	35.2%	39.6%
	Master's	49.1%	38%	37%	39.6%
	Doctoral	13.2%	18%	27.8%	20.8%
Upbringing	Rural	11.3%	6%	16.7%	17%
	Urban	88.7%	94%	83.3%	83%

Residency	Non-resident	9.4%	16%	11.1%	11.3%
	Resident	90.6%	84%	88.9%	88.7%
N		53	50	54	53

Note: Standard deviation in parentheses.

Table B4 (filtered sample)

		Group A	Group B	Group C	Group D
Interest in politics		6.1 (2.76)	6.49 (2.56)	6.77 (2.22)	6.11 (2.6)
Trust in government		4.34 (1.92)	3.78 (1.8)	5.11 (1.91)	4.09 (2.27)
Familiarity with AI		7.1 (1.48)	7.56 (1.98)	7.71 (1.67)	7.2 (1.75)
Attitude toward AI		6 (2.11)	6.71 (2.41)	6.69 (2.03)	5.61 (2.36)
Gender	Male	41.5%	39%	45.7%	58.7%
	Female	58.5%	58.5%	54.3%	41.3%
	Prefer not to say	0%	2.4%	0%	0%
Age	18–24	61%	51.2%	51.4%	69.6%
	25–34	34.1%	34.1%	34.3%	21.7%
	35–44	4.9%	14.6%	14.3%	8.7%
Field of study	Non-STEM	48.8%	48.8%	60%	41.3%
	STEM	48.8%	48.8%	34.3%	54.3%
	Not sure	2.4%	2.4%	5.7%	4.3%
Academic program	Bachelor's	41.5%	39%	34.3%	39.1%
	Master's	43.9%	43.9%	37.1%	41.3%
	Doctoral	14.6%	17.1%	28.6%	19.6%
Upbringing	Rural	12.2%	7.3%	20%	15.2%

	Urban	87.8%	92.7%	80%	84.8%
Residency	Non-resident	7.3%	17.1%	14.3%	8.7%
	Resident	92.7%	82.9%	85.7%	91.3%
N		41	41	35	46

B.1.4. Manipulation check

Table B5 (full sample)

Group	N	Competence		Benevolence	
		Mean	SD	Mean	SD
High competence (A)	53	5.17	1.77	4.52	2.10
High benevolence (B)	50	4.86	1.88	4.70	2.08
High competence and benevolence (C)	54	5.39	1.88	4.95	2.12
Control (D)	53	4.82	1.69	4.31	2.08

Table B6 (filtered sample)

Group	N	Competence		Benevolence	
		Mean	SD	Mean	SD
High competence (A)	41	5.24	1.85	4.56	2.20
High benevolence (B)	41	4.70	1.94	4.50	2.17
High competence and benevolence (C)	35	5.94	1.45	5.30	1.93
Control (D)	46	4.73	1.78	4.25	2.20

B.1.5. Difference-in-means test

Table B7 (full sample)

Group	Mean	Difference from control group	p-value
Control (D)	5.77		
High competence (A)	5.59	-0.18	0.72
High benevolence (B)	6.00	+0.23	0.65
High competence and benevolence (C)	6.23	+0.45	0.35

Table B8 (filtered sample)

Group	Mean	Difference from control group	p-value
Control (D)	5.65		
High competence (A)	5.55	-0.10	0.86
High benevolence (B)	5.82	+0.17	0.77
High competence and benevolence (C)	6.48	+0.83	0.16