

Digital Transformation of Public Services: A Multi-Level Analysis of E-Government,
M-Government, and Smart Government

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Abstract

This thesis examines the impact of digital transformation on public service by analyzing multi levels; e-government, m-government and smart government across three papers. The first paper examines the role of external rewards in e-government services adoption in Jordan, extending the Unified Theory of Acceptance and Use of Technology (UTAUT) to include external rewards as an extrinsic motivator, using national survey data, the results revealed that external rewards significantly increase citizens' likelihood of e-government adoption when moderated by demographics and digital skills. The second paper explores how the citizen sentiment toward the national m-government application in Jordan is affected by media announcements, mandatory adoption, and different stages of the app development, by analyzing over 10,000 user reviews through sentiment analysis, topic modeling, regression, and fsQCA, it shows that app improvements and positive media framing enhance the public sentiment, while mandatory adoption raises resistance. The third paper investigates why countries lag behind AI implementation despite their AI readiness, proposing an extended TOE-G framework that incorporates governance alongside technology, organization, and environment, using data from 77 countries, the results revealed that while technological and environmental factors drive AI implementation, excessive governance may negatively affect the progress. Collectively, these papers contribute to the literature on e-government, m-government, and smart government by offering multi-level insights for policymakers to improve the adoption of public services.

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Chapter 1: Introduction

Digital transformation is on the agenda of policymakers around the world, and governments have been fast-moving towards digitization in the last decade. Diverse types of technologies are being introduced such as; big data, internet of things, cloud computing, social media, mobile computing, and artificial intelligence, with those technologies the digital transformation in government is entering a new age (Dijck, José, and De Waal 2018). Governments today aim to enhance its services in through digital transformation initiatives (Goh & Arenas, 2020). Public organizations' main goal is to increase public values such as legitimacy, lawfulness, accountability and justice compared to the private sector focused on profitability, competitiveness, customer relationship and revenue generation (Goh & Arenas, 2020). Further, technologies have become widely used in the public sector and nowadays it's impossible to think about a government service that does not involve technology in substantial ways (Ramon et al., 2018).

Additionally, technologies are becoming much smarter with the integrative platforms of digital government in which data and information are easily connected to each other (Kim et al, 2022). Technology-based platforms are increasingly used by governments worldwide to enable public engagement with citizens (Jiang et al.,2019), and governments are moving towards digitalized services to earn the benefits associated with the information technology such as efficiency and cost savings (Osman et al.,2019; Kim et al., 2021; Ruijer et al., 2022; Ramirez-Madrid et al., 2022), productivity (Goh & Arenas, 2020; Maclean & Titah, 2021), echoing the private sector technological advancements (Schiff et al., 2021) and increase their

competitiveness stake (Dunleavy et al. 2006; Castelnovo & Sorrentino, 2018); Giest & Klievink, 2022). Moreover, developing countries are under the pressure to move towards e-government and adopt the western context of IT development as part of their development and modernization projects (Addo, 2021).

The digital transformation is accompanied by the use of tools, applications, and emergent technologies such as; mobile applications, open data, social media, technical and organizational networks, the Internet of Things, sensors, data analytics, and more (Ramon et al., 2018). In the past two decades, digital transformation in governments took various forms, starting from developing websites to help citizens accessing government services (Ngwenyama et al., 2021; Larsson & Skjølsvik, 2021), government open data (Lember et al., 2019; Mu & Wang, 2020; Ruijer et al., 2022) and designing mobile applications (Gil-Garcia et al., 2018; Mu & Wang, 2020; Lekkas & Souitaris, 2022) moving to the new wave of technology and applying artificial intelligence using chatbots to engage with citizens (Larsson & Skjølsvik, 2021; Dickinson & Yates, 2021; Maragno et al., 2022), applying AI algorithms in predictive modeling to support decision making (Dickinson & Yates, 2021; Schiff et al., 2021) and routine assessments for public claims (Giest & Klievink, 2022; Gaozhao et al., 2023). Additionally, governments applied Internet of Things techniques in the smart cities (Kim et al., 2021; Lekkas & Souitaris, 2022; Kraus et al., 2022).

Further, governments are investing more in artificial intelligence (AI) to improve public services (Hjaltalin et al., 2024) and the smart government is considered the highest modernization phase of public services (Hujran et al., 2023). AI is a key

enabler for digital transformation, mainly in the smart government, for instance, utilizing chatbots (Androutsopoulou et al., 2019; Desouza et al., 2020), AI-based self-service technology (Chen et al., 2021), AI voice robots (Wang et al., 2021), predictive analytics systems for fraud detection (Desouza et al., 2020; Chatterjee et al., 2022), and networked camera to detect theft and criminals (Yigitcanlar et al., 2023) supports how governments can achieve improved levels of communication with citizens, improved citizens' experience, significantly decreases the administrative load of public organizations, achieving cost efficiencies (Androutsopoulou et al., 2019; Chen et al., 2021, Hujran et al., 2023). Furthermore, the shift towards smart government enables real-time data-driven, more responsive public services, and increased citizen engagement, this includes balancing innovation with privacy concerns, facilitating equitable access to digital services, and enhancing public trust in automated systems (Terán et al., 2024).

Despite the potential benefits that the digital transformation of public services can bring for both government and citizens, the widespread adoption of digital public services remains a challenge (Ramirez-Madrid et al., 2022; Ma & Zheng, 2018), and nearly half of countries are below the worldwide average in the digitalization of their public services (United Nations, 2022), figure 1 below, shows the percentage of countries below the worldwide average in the digital transformation indices of the UN e-government survey for the year 2022:

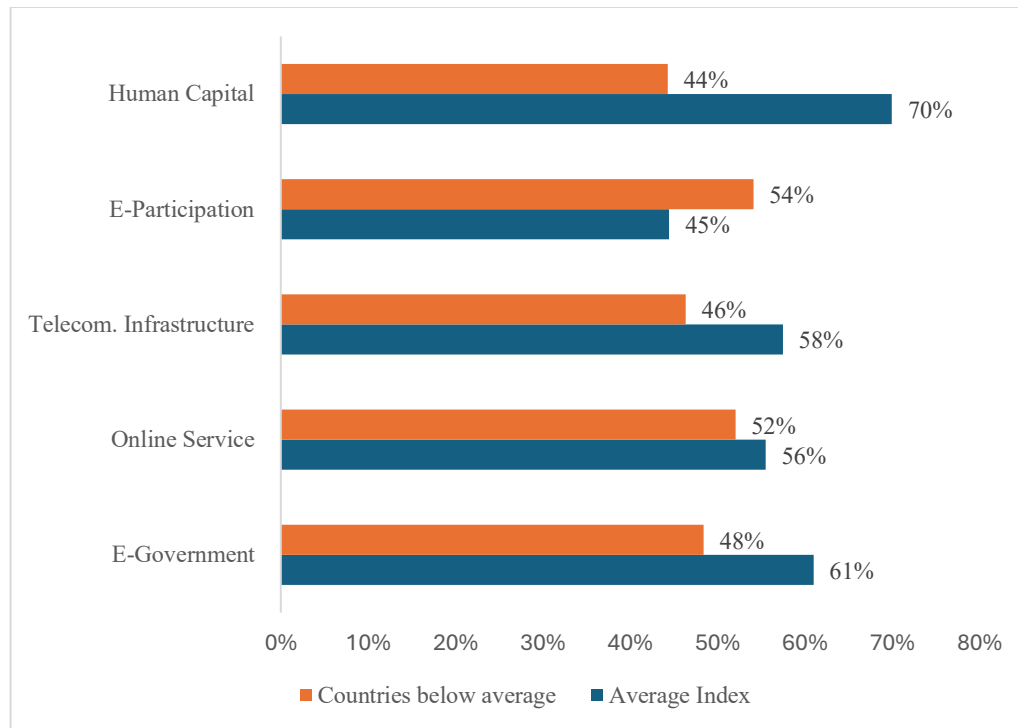


Figure 1: Percentage of countries below the average of UN-e-government survey indices

Further, research related to the digital transformation of the public sector is still in early stages (Appio et al., 2021; Lanzolla et al., 2021; Kraus et al., 2022), in specific for the recent wave of technologies (Dickinson & Yates, 2021; Kim et al., 2021; Menz et al., 2021). Scholars called for more research in the domain of digital transformation in the public sector and its impact (Vial, 2019; Larsson & Skjølsvik, 2021; Palumbo, 2022; Kim et al., 2021; Dickinson & Yates, 2021).

Current digital transformation research for the public sector overlooks how various factors such as extrinsic motivation, media framing, and governance structures can shape technology adoption and implementation, where high AI readiness often fails to translate into actual implementation. This thesis addresses how external rewards, media framing, technology, organization, environment, and governance impact the

digital transformation in the public sector mainly– e-government, m-government, and smart government, and aims to answer the research question of:

RQ: How do external rewards, media framing, and governance frameworks shape the adoption and implementation of digital public services?

1. E-Government

E-Government involves utilizing technology tools to improve the efficiency in providing the services to citizens (Iannaccia et al., 2019) and includes providing services by government to citizens through information technology (IT) and mainly via the Internet (Maclean & Titah, 2021). Governments are keen to use e-government services for various reasons; transform the future of the delivery of public services (Barbosa et al., 2013), efficiency and cost savings (Osman et al., 2019; Kim et al., 2021; Ruijer et al., 2022; Ramirez-Madrid et al., 2022), productivity (Goh & Arenas, 2020; Maclean & Titah, 2021), echoing the private sector technological advancements (Schiff et al., 2021) and increase their competitiveness stake (Dunleavy et al. 2006; Castelnovo & Sorrentino, 2018); Giest & Klievink, 2022). The Danish government provided an interesting example of e-government illustrated by the Danish NemID, which is a personal digital identifier for Danish citizens, and it is necessary for home-banking and access to all Danish government services (Ngwenyama et al., 2021). On the other side, Addo (2022) discussed the e-government in India, a developing country, illustrated by website of Aadhaar; the largest government-orchestrated platform ecosystems in the world and provides digital identity to enable access to a range of e-government services. Further, the importance of e-government is

recognized worldwide; the United Nations (UN), placed it at the center of its 17 Sustainable Development Goals for 2030 (United Nations, 2018).

The digital transformation of public services comes with various benefits, however, the world is still witnessing low adoption rates of e-government (Venkatesh et al., 2016; Osman et al., 2019), specially in developing countries characterized with weak technology development due to many challenges such as demographic changes; expanding and younger populations, which in turn increase the supply of labor and decrease wages, reducing the incentives for automation, weak financing mechanisms for technologies, in addition, to income poverty, digital divide and shortage of skills (UNCTAD, 2021). According to the United Nations, in 2019, only 47 percent of individuals in developing countries were online, compared to 87 percent in developed countries (ITU, 2019). The underutilization of e-government services can in turn affect governments in realizing the full benefits related to cost savings and efficiency improvements (Venkatesh et al., 2016). Low e-government adoption rates could be attributed to the digital divide, as compared to developed economies, the digital divide in developing countries is more pronounced due to infrastructure limitations, with unreliable access to high-speed internet, electricity, and digital devices, especially in rural areas. Socio-economic disparities and higher poverty levels further restrict access to digital technologies, while limited financial and administrative resources hinder the implementation of large-scale digital initiatives.

Previous literature has established a link between motivation and the adoption of an activity (e.g., Krishnamurthy et al., 2014). In the context of information systems, previous studies highlighted the significance of extrinsic motivators, such as

performance expectancy, in user adoption (Malhotra et al.,2008; Petter et al.,2013), the e-government paper focus on the external rewards in specific as an extrinsic motivator for e-government service adoption, an unexplored factor in the literature.

2. *M-Government*

M-government is a subset of e-government and refers to the government's use of mobile and wireless technology to deliver its services (Chen et al.,2016). Unlike traditional e-government platforms, m-government services can reach citizens in remote areas using mobile internet and pre-installed applications (Liu et al.,2014). M-Government reflects the applications of mobile devices in the public administration context (Wirtz et al., 2021). Additionally, it extends e-government applications to mobile and wireless channels (Sheng & Trimi, 2008).

M- government services have a number of distinct features including affordability, reachability, ubiquity, timely information delivery, low digital literacy requirement, personalized information delivery, and emergency management capabilities (Liu et al.,2014). Beyond these benefits, the m-government enhances the scope of delivery of government services, both geographically and in terms of the number of people regardless of the wired technology infrastructure, increases the efficiency and effectiveness of government employees, and facilitates better citizen participation in decision making (Sheng & Trimi, 2008; Abu-Shanab & Abu-Tair, 2014). Due to the advancements in mobile technology and the demand for more responsive government services, public organizations all over the world are seeking to leverage mobile

technologies to provide services to citizens (Sheng & Trimi, 2008). M-government emerged with the recent advancements of the network's infrastructure and mobile computing techniques (Al-Hujran, 2012) and makes a technology-driven government service more mobile, dynamic, accessible, and available (Shareef et al., 2016). However, successful m-government implementation requires governments to carefully monitor and analyze end-users' wants and their perceived benefit from using m-government applications (Sheng & Trimi, 2008).

M-government solves the challenges associated with the traditional e-government, particularly in developing economies where the high implementation and infrastructure costs, limited access to computer equipment, high Internet fees, as well as low digital literacy have hindered digital service adoption (Liu et al., 2014). In many of these regions, the rapid growth of mobile phone usage has provided a cost-effective alternative to conventional e-government platforms (Liu et al., 2014). This shift has led to the concept of "technology leapfrogging," where developing countries bypass earlier technological stages and adopt more advanced solutions directly (Davison et al., 2000). Leapfrogging allows developing countries such as Jordan to achieve advanced state of information and communications technology connectivity rapidly without following the traditional phased development of digital infrastructure (Ng & Tan, 2018; Tan et al., 2018).

Despite the advancements in m-government, its success is highly dependent on citizen adoption and satisfaction, which are influenced by multiple factors, including ease of use, functionality, perceived trust, and government communication strategies (Wirtz et al., 2021; Almarashdeh & Alsmadi, 2017). Many initiatives struggle with

user dissatisfaction, technical challenges, and public resistance to adoption (Mossey et al., 2019). One major obstacle is the lack of a citizen-centric approach in m-government service design, as governments often prioritize technological development over understanding the needs and expectations of users (Kowalski et al., 2020). Without integrating citizen feedback, government-led digital services may fail to achieve widespread acceptance and positive public engagement.

In parallel, media plays a crucial role in shaping public perceptions of government initiatives (Sembor, 1993), and with the rise of social media and user-generated data, citizens now express their opinions dynamically through online platforms, including mobile app reviews, providing a rich and underutilized source of public sentiment data, the m-government paper address the gaps in literature by integrating insights from public opinion research, media framing theory, and sentiment analysis to examine the evolution of citizen sentiment toward m-government services.

3. Smart Government

Smart government refers to the government activities related to creatively investing in emerging technologies along with innovative strategies to achieve agile resilient services and structures, becoming a smarter government requires having a forward-thinking approach to use and integrate information, technology, and innovation (Gil-Garcia et al., 2014), in addition to organizing the initiatives leading towards modernization and reorganization of the public affairs (Bojović et al., 2023). The ultimate goal of smart governments is to create a sustainable, citizen-focused governance model that can adapt to the citizens changing needs on a real-time basis (Terán et al., 2024). The smart government has a set of features: integration,

innovation, evidence-based decision making, citizen-centric, sustainability, creativity, effectiveness, equality, openness, resilience, and technology savviness (Algebri et al., 2017).

Smart government is getting increasing attention from researchers and practitioners in recent years being viewed as the next revolution in the e-government domain (Algebri et al., 2017; Anthopoulos et al., 2022; Hujran et al., 2023; Bojović et al., 2023), and the use of smart technologies in the public sector (i.e. blockchain, IoT and AI) are expected to grow in both importance and actual use in the next few decades (Criado & Gil-Garcia, 2019), making public administration more intelligent and agile (Bojović et al., 2023). Smart government is the modern form of e-government, transforming the digital government to more agile, effective and efficient one (Anthopoulos et al., 2021), compared to e-government and m-government that focus mainly on providing the public services through the internet and wireless technology, smart government not only aims to digitalize public processes, but it also seeks to largely rethink the way government operates, which shall transform the relationship between citizen and government (Schedler, Guenduez, & Frischknecht, 2019). Further, Smart government could enhance the delivery and efficiency of government services and information, due to easier access and availability for citizens (Althunibat et al., 2021), additionally, computational models, including government analytics, big data, policy modeling, and artificial intelligence, shall support the future development of public services (Criado & Gil-Garcia, 2019).

Despite the numerous benefits of AI implementation as enabler to smart government, the average implementation score of AI according to the Global AI index

is only 13%, having United States and China at the top of index with score of 100%, and 54%, respectively, and the remaining countries in the index with scores below 50% (Tortoise Media, 2024), further the average AI readiness capabilities for those countries is 72% and majority of the countries had scores exceeding 50%, which shows a significant deviation between the actual AI implementation by governments compared to their AI readiness capabilities.

Research Questions

The thesis addresses different levels of digital transformation of public services, mainly the e-government, m-government, and smart government, and aims to answer the following research questions:

1. What role does extrinsic motivation, specifically monetary reward, play in driving the adoption of e-government services in Jordan?
2. What are the key themes and sentiments expressed in citizen opinion presented in the reviews of the m-government application and how does the citizens' sentiment evolve through various stages of the application development?
3. How do different actions by policymakers shape public opinion, including newspaper announcements, mandating the use of the app, and the evolution of the app through various stages?
4. Why do countries lag behind the actual AI implementation despite their AI readiness?

The thesis adds to the growing literature related to the various forms of public sector transformation; the e-government, m-government and smart government, by exploring the factors driving citizen adoption, it bridges an important gap in the

current understanding of e-government dynamics, additionally, while most studies focus on developed economies, our research sheds light on e-government challenges in developing economies, by exploring the unique socio-economic landscapes of these countries, it contribute context-specific insights that are crucial for policy formulation and implementation in similar contexts, it advances research on citizen sentiment analysis in public service management by showcasing the potential of computational techniques to extract meaningful insights from large-scale user-generated data, Second, it offers new insights by extending the technology adoption theories such as UTAUT, emphasizing the role of extrinsic motivation as a driver of the adoption of e-government services and expanding the UTAUT theoretical framework by adding the external reward as an extrinsic motivating factor to the model, offering a more comprehensive understanding of the factors shaping e-government users' behavior. Further, it extends media framing theory by applying it to the domain of digital government services, demonstrating how government announcements and news framing impact public attitudes toward technology adoption, and it highlights the importance of the governance dimension in AI implementation, by extending the TOE framework offering a key theoretical contribution to the existing TOE framework to the new TOE-G framework. Third, it contributes to the literature with empirical evidences, answering the calls for more quantitative research in digital transformation.

Thesis Datasets

The thesis used several datasets to answer the research questions associated with the e-government, m-government, and smart government challenges:

1. E-Government

The thesis used the data from Jordan's 2021 Technology and Internet Survey, which comprises of 10,703 individuals. The dataset includes the responses to a questionnaire prepared by the Ministry of Digital Economy and Entrepreneurship in Jordan. The purpose of the survey was to identify the spread of technology and the Internet across Jordan, in addition to the use of technology to access e-government services through different means such as websites, mobile applications, electronic booths, and knowledge stations. The data was collected in the fourth quarter of 2021 by a team of researchers from the Ministry and the Jordanian Department of Statistics. The data collection team included field officers, researchers, supervisors, and data quality auditors. The researchers visited the households and collected the data directly from everyone in the household.

2. M-Government

For the M-Government part, the thesis utilized two datasets. The first dataset comprised 10,725 user reviews of the m-government application, extracted from the Google Play Store, along with their respective dates and app versions. The reviews spanned from September 2020 to December 2023. The second dataset included media announcements related to the Sanad application, containing the news agency source, date, title, and full content.

3. Smart Government

For the smart government, we created a dataset from different international indices, we used the implementation to readiness ratio from the AI readiness index and the Global AI index for the year 2024, we also included variables covering the three dimensions of the TOE framework, and the governance dimension, the variables were extracted from the UN E-Government Survey 2024, Worldwide Governance Indicators from the World Bank, and Global Innovation Index. The dataset includes 77 countries.

Outline

This thesis is composed of three empirical studies, presented in Chapters 2, 3 and 4, in which the above-mentioned research questions are explored. Each Chapter provides an introduction, literature reviews, the methodology, results, discussion, and lastly provides a conclusion. Each of these three chapters can be read independently from the other chapters. Chapters 2 and 3 discuss the demand side of the digital transformation focusing on e-government and m-government, while Chapter 3 shows the supply side for the most advanced type of public transformation; the smart government. Finally, Chapter 5 provides a review of the main findings, discusses the implications of the thesis for both policymakers and scholars, and proposes directions for future research.

Chapter 2

Exploring the impact of external rewards on e-government services adoption: empirical evidence from Jordan

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Abstract

This research investigates how external rewards influence citizens' adoption of e-government services in Jordan, using data from the 2021 Technology and Internet Survey. Extending the UTAUT model, it incorporates external rewards as an extrinsic motivator. Findings show rewards significantly impact adoption, varying by location, age, income, education, and digital skills. It contributes to understanding e-government demand and offers policymakers strategies to increase adoption rates, fostering a more inclusive digital ecosystem.

Keywords: e-government, e-services, digital services, adoption, public sector, government, UTAUT, digital transformation, digitalization, extrinsic motivation, external rewards. digital divide, digital inequality, digital skills

Introduction

Information technologies have become integral to public sector operations, transforming the way governments deliver services and engage with citizens (Gil-Garcia et al., 2018; Furr et al., 2022). Around the world, governments are increasingly utilizing digital platforms to streamline public engagement and service provision (Jiang et al., 2019). Governments are moving towards digitalized services to gain the benefits associated with information technology, such as efficiency and cost savings (Osman et al., 2019; Kim et al., 2021; Ruijter et al., 2022; Ramirez-Madrid et al., 2022), higher productivity (Goh & Arenas, 2020; Maclean & Titah, 2021), increased competitiveness (Dunleavy et al., 2006; Castelnovo & Sorrentino, 2018; Giest & Klievink, 2022), echoing the private sector technological advancements (Schiff et al., 2021).

Despite the potential benefits, widespread adoption of e-government services remains a challenge (Ma & Zheng, 2018; Piehler et al., 2016), particularly in developing countries (Ramirez-Madrid et al., 2022). According to the United Nations, in 2019, only 47 percent of individuals in developing countries were online, compared to 87 percent in developed countries (ITU, 2019). As compared to developed economies, the digital divide in developing countries is more pronounced due to infrastructure limitations, with unreliable access to high-speed internet, electricity, and digital devices, especially in rural areas. Socio-economic disparities and higher poverty levels further restrict access to digital technologies, while limited financial and administrative resources hinder the implementation of large-scale digital initiatives. Additionally, economic instability and regional conflicts strain resources,

making it harder for citizens, particularly those relying on government aid to access services through digital platforms. This disparity highlights the pressing need to better understand the barriers to e-government adoption in developing economies.

From the perspective of the demand side, low e-government adoption rates could be attributed to the digital divide (Abu-Shanab & Khasawneh, 2014; Botrić & Božić, 2021). The term digital divide indicates that disadvantaged groups of the population are denied access to technology (Robinson et al., 2003). Different types of inequalities can cause digital divides such as life chances, economic and social conditions, skills, and capabilities (Van Dijk, 2006). Notably, the digital divide is more evident in the developing countries due to lack of human and technical infrastructure, low acceptance rates of technology, and inadequate institutional cooperation and information sharing mechanisms (Kim & Park, 2018).

Disadvantaged groups can suffer in different ways from the technology exclusion including hindering their ability to acquire knowledge, access educational materials, develop essential skills, participate in the digital economy, connect with society, access online exclusive benefits, civic engagement and political participation (Charles et al., 2024), leaving a significant gap between these groups and those who are more privileged. Bridging this divide is crucial for promoting digital inclusion and ensuring that the benefits of e-government services are accessible to all citizens, particularly those from disadvantaged backgrounds.

Given these challenges, this study explores the role of extrinsic motivation as a strategy to incentivize e-government adoption among disadvantaged groups. Extrinsic motivation refers to the performance of a certain activity to obtain an external reward

(Deci, 1972), which serves as a positive reinforcer for a desired behavior (Bénabou & Tirole, 2003). External rewards refer to incentives that can make people wealthier and materially successful if they meet the criteria for receiving the reward (Kasser and Ryan 1996). External rewards are significantly associated with the people's behaviors and the choices they make, external rewards tend to have high outcomes since money is tangible, further, the reward type whether financial, recognition or social can have different impacts on behaviors depending on the timing of reward, conditions of uncertainty and relationship with intrinsic motivation. (Malek et al., 2020).

In developing countries like Jordan, where digital literacy and access to technology are limited, external rewards can serve as critical drivers to encourage citizens to engage with digital platforms. These rewards help bridge the motivational gap for individuals who may not perceive immediate benefits from adopting e-government services, thus playing a vital role in increasing adoption rates. For disadvantaged populations, offering tangible rewards—such as monetary incentives—may encourage the use of digital government services, helping to reduce inequalities in access (Voigt, 2017). In the context of information systems, extrinsic motivators like performance expectancy have been shown to significantly influence technology adoption (Malhotra et al., 2008; Petter et al., 2013). However, the role of external rewards—particularly monetary incentives, driving e-government adoption in developing countries remains underexplored (AlHadid et al., 2022; Rabaa'i, 2017).

To address this gap, this paper investigates the impact of extrinsic motivation, specifically monetary rewards, on e-government adoption in Jordan, a developing

country characterized by significant socio-economic disparities. Specifically, we seek to answer the following research questions:

1. What role does extrinsic motivation, specifically monetary rewards, play in driving the adoption of e-government services in Jordan?
2. How can external rewards help disadvantaged groups overcome barriers to adopting e-government technologies?

This paper is framed within the unified theory of acceptance and use of technology (UTAUT) model, a widely used framework in technology adoption. While previous research has focused primarily on performance expectancy, effort expectancy, and social influence as drivers of e-government adoption, we extend the model by incorporating external rewards—an underexplored construct in this context. Unlike performance expectancy, external rewards provide tangible incentives, such as monetary benefits, that go beyond expected service quality. Prior studies have shown that monetary incentives can significantly increase user engagement with digital platforms in other domains (Camera et al., 2016; Sun et al., 2019).

We employ data from Jordan's 2021 Technology and Internet Survey, which comprises of 10,703 individuals. Jordan presents a unique context for this study: while urban centers in the country enjoy modern infrastructure and a growing middle class, rural areas face significant challenges, including limited access to education, healthcare, and employment opportunities (World Bank, 2023). Additionally, the influx of refugees from neighboring conflict zones has further strained resources and exacerbated socio-economic disparities. These factors contribute to a pronounced

digital divide, making Jordan an ideal case for studying the impact of external rewards on e-government adoption.

Our findings show that external rewards significantly increase the likelihood of e-government adoption, particularly among disadvantaged groups, such as rural residents, low-income individuals, and the elderly. We also find that factors such as geographic location, income, and digital skills moderate the relationship between external rewards and e-government adoption.

This paper contributes to the literature in several ways. First, it adds to the demand-side in e-government research by examining how extrinsic motivators, specifically monetary rewards, influence citizen adoption. Second, it extends the UTAUT model by incorporating external rewards as a unique construct, offering new insights into how disadvantaged groups in developing countries can be incentivized to adopt e-services. Third, while much of the existing research focuses on developed economies, our study provides context-specific evidence from Jordan, a developing country, contributing to a more nuanced understanding of e-government challenges in similar regions. Finally, this study provides large-scale empirical evidence using data directly collected by the government, answering calls for more quantitative research in the field of digital transformation (Goh & Arenas, 2020; Addo, 2021; Larsson & Skjølsvik, 2021; Schiff et al., 2021; Lekkas & Souitaris, 2022; Giest & Klievink, 2022).

Literature Review

Technology has been an essential element in shaping changes in public management for several decades (Dunleavy et al., 2006; Maclean & Titah, 2021).

Governments all around the world are under constant pressure to make improvements in their internal processes and public services (Dickinson & Yates, 2021), as the rise of data-driven systems suggests a new public service delivery regime (Giest & Klievink, 2022) and digital reforms and modernization projects have become a priority on the political agenda of governments (Barbosa et al., 2013). The importance of e-government is recognized worldwide; the UN, placed it at the center of its 17 Sustainable Development Goals for 2030 (United Nations, 2018).¹

In the past two decades, digital transformation in governments took various forms, starting from developing websites to help citizens accessing government services (Ngwenyama et al., 2021; Larsson & Skjølsvik, 2021), government open data available freely to the public (e.g. climate data, energy data, and transportation data) (Mu & Wang, 2020; Ruijter et al., 2022) and to designing mobile applications to improve public services (Gil-Garcia et al., 2018; Lekkas & Souitaris, 2022). More recently, advances have included applying artificial intelligence to chatbots to engage with citizens (Larsson & Skjølsvik, 2021; Dickinson & Yates, 2021; Maragno et al., 2022), and routine assessments for public claims (Giest & Klievink, 2022; Gaozhao et al., 2023). Additionally, governments are applying Internet of Things techniques in smart cities (Kim et al., 2021; Lekkas & Souitaris, 2022; Kraus et al., 2022).

In this context, the concept of e-government includes providing services by a government to citizens through information technology and mainly via the Internet

¹ The Sustainable Development Goals (SDGs), were announced by the United Nations in 2015 as a universal call to action to make the world a better place by ending poverty, protecting the planet, and ensuring that all people enjoy peace and prosperity by 2030. Jordan scored 69 out of 100 in the UN sustainable development goals report, and none of the SDGs were achieved in Jordan; despite the country had fair progress, acceleration is needed (United Nations, 2023).

(Maclean & Titah, 2021). Governments are keen to use e-government services for various reasons including the transformation of the future of the delivery of public services (Barbosa et al., 2013; Gupta, et al.,2008), simplifying work arrangements and reducing the need for manual labor work (Addo, 2021; Goh & Arenas, 2020; Kim et al., 2021; Dickinson & Yates, 2021), efficiency and cost savings (Osman et al.,2019; Kim et al., 2021; Ruijter et al., 2022; Ramirez-Madrid et al., 2022), productivity (Goh & Arenas, 2020; Maclean & Titah, 2021), improved interaction with business and industry (Gupta et al.,2008), employee and citizen empowerment (Gupta et al.,2008; Lember et al., 2019; Larsson & Skjølsvik, 2021), offering new means for the governments to produce value for citizens (Larsson & Skjølsvik, 2021), changed decision making process (Lember et al., 2019; Kim et al., 2021; Giest & Klievink, 2022), removal of bureaucrats personal bias in dealing with citizens (Miller et al., 2021; Gaozhao et al.,2023), and improvements in the citizen–government relationship by increasing the citizen’s trustworthiness of government (Maclean & Titah, 2021).

Previous literature has explored different aspects of e-government both on the supply and demand side. On the supply side, scholars explored the barriers to digital transformation, such as bureaucracy (Addo, 2021; Goh & Arenas, 2020), public servants’ resistance, and fear of job loss (Addo, 2021; Dickinson & Yates, 2021; Noesgaard et al., 2023), weak commitment to organizational change (Addo, 2021), weak competencies and technical skills (Hu, 2018; Mu & Wang, 2020), inflexible standard operating procedures, limited government capabilities to sustain innovation

over time (Mu & Wang, 2020), and lack of legal and regulatory frameworks (Furr et al., 2022).

On the demand side, previous literature analyzed citizen's adoption from different aspects such as trust (Chan et al., 2010; Porumbescu, 2016; Venkatesh et al., 2016; Janssen et al., 2018; Ramirez-Madrid et al., 2022). e-participation (Lee & Kim, 2018; Jiang et al., 2019; Van Den Berg et al., 2020), co-production and co-creation (Lember et al., 2019; Xu & Tang, 2020; Larsson & Skjølsvik, 2021), citizens' privacy concerns (Willems et al., 2022), and the impact of system quality characteristics on citizens' perceptions (Scott et al., 2016; Piehler et al., 2016; Chan et al., 2021).

Both the supply and demand side in the developing economies experience challenges due to the digital divide, as these countries are under pressure to move towards e-government and adopt the Western context of IT development as part of their development and modernization projects (Addo, 2021). The digital divide separates nations and individuals, therefore, recognizing this divide is key to empowering citizens' participation and technology adoption (Okunola et al., 2017). The digital divide refers to the difference in the adoption and use of digital technologies according to demographic characteristics, such as age, gender, race, income level, and location (Charness & Boot, 2022). The existence of the divide can limit the success of e-government programs (Asgarkhani, 2005). Developed nations such as West Europe and the US remain at the top of the digital development index while developing countries including Jordan struggling at the bottom (UN, 2022), the technology infrastructure index in the developing countries is 44% compared to 84% in the developed countries (UN, 2022). The digital divide in developing regions

resulted from the high cost of building and maintaining the technology infrastructure, the monopoly of telecommunication providers, and the cultural norm where citizens prefer in-person interactions (Zhao et al., 2018).

In light of the above, the gap remains in the demand side of e-government (Lee & Kim, 2018; Ma & Zheng, 2018), especially in the developing countries struggling to bridge the digital divide (Avgerou & Bonina, 2020; Kraus et al., 2022; Addo, 2021), and the factors driving e-services adoption (Lee & Kim, 2018; Van Den Berg et al., 2020).

Theoretical Framework and Hypotheses

Theoretical Framework: UTAUT

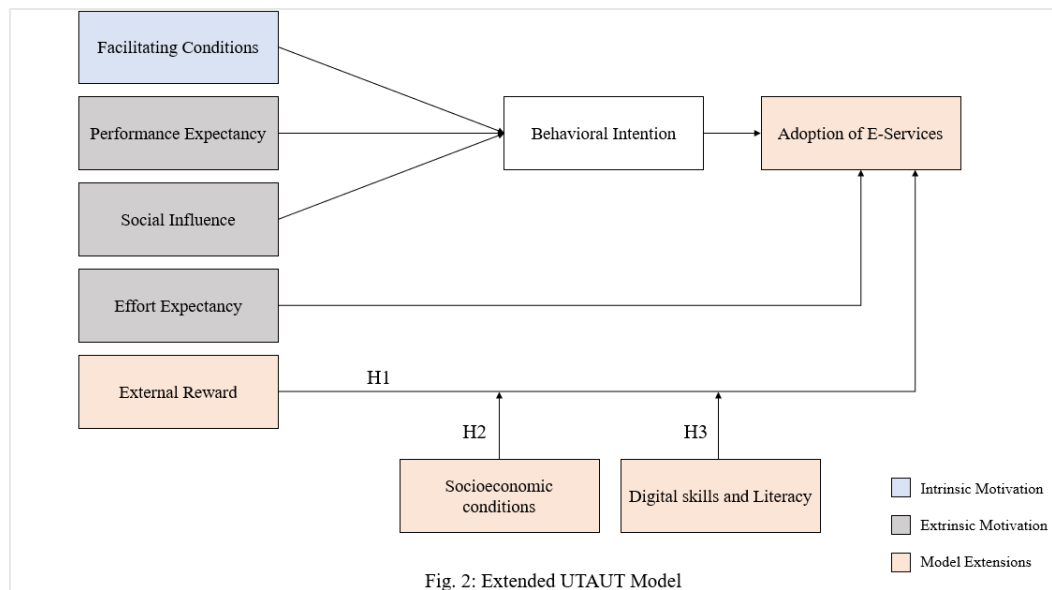
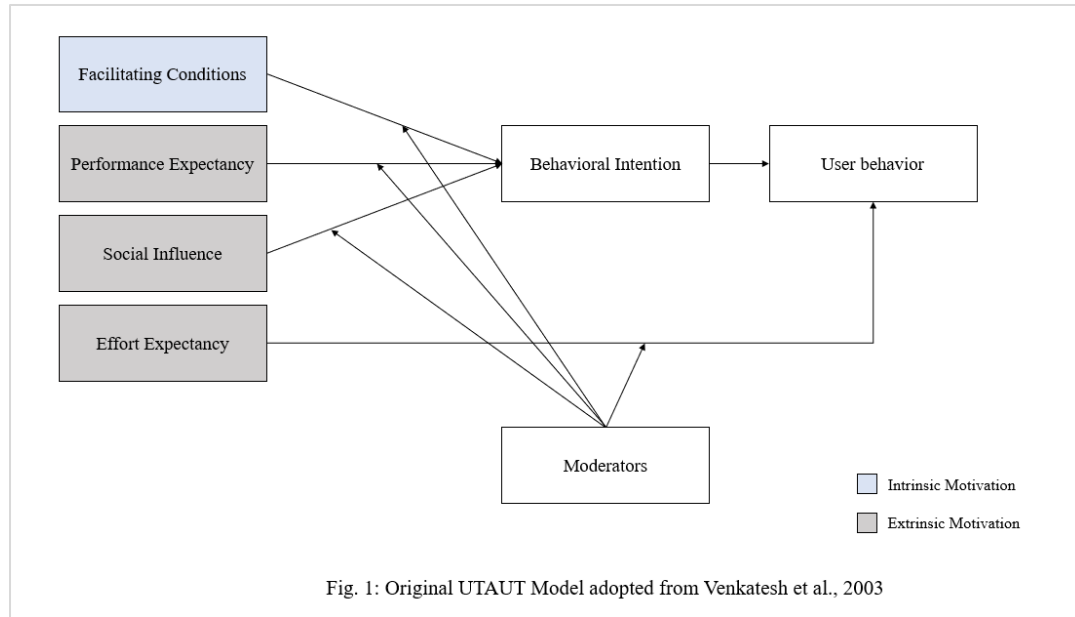
The UTAUT is one of the most widely used frameworks in technology adoption research, it was introduced by Venkatesh et al., (2003) and it combines eight technology acceptance models and frameworks; Theory of Reasoned Action, Technology Acceptance Model (TAM), Motivational Model, Theory of Planned Behavior (TPB), Combined TAM and TPB, Model of Personal Computer utilization, Innovation Diffusion Theory and Social Cognitive Theory (Venkatesh et al., 2003). The model includes four main factors: performance expectancy, effort expectancy, social influence, and facilitating conditions, and four moderators (age, gender, experience, and voluntariness) related to identifying the behavioral intention for technology use and adoption. Performance expectancy is the benefits expected by the users when performing a certain activity using technology, effort expectancy is the ease of use associated with the technology, social influence is the extent to which the user feels that it's important that others believe he or she should use the technology,

and facilitating conditions includes the organizational and technical infrastructure supporting the use of technology (Venkatesh et al., 2003).

While UTAUT provided valuable insights into users' technology acceptance by focusing on the main constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions, the previous research conceptualized the extrinsic motivation in the performance expectancy, effort expectancy and social influence constructs (see Figure 1).

Previous literature has noted that this model may not provide a comprehensive understanding of the impact of user motivation on information system adoption (Malhotra et al., 2008; Petter et al., 2013) and has called for the addition of further elements into the model (Blut et al., 2021). While performance expectancy, effort expectancy, and social influence are established extrinsic motivators in the UTAUT framework, our research extends this model by focusing on external rewards as a distinct form of extrinsic motivation. External rewards refer to tangible incentives, such as monetary benefits, that are not inherently tied to the perceived performance of the e-government service but rather provide direct and immediate benefits for using the system. This is distinct from performance expectancy, which emphasizes improvements in service quality or user outcomes. For example, an external reward in the context of e-government services might include financial incentives like tax credits or waived fees, which provide a direct, tangible benefit upon usage of the service. This differentiation is particularly important in the context of developing countries, where socio-economic disparities may mean that financial incentives have a greater influence on adoption than perceived service quality alone. In the next

section, we discuss the addition of external reward as an additional construct to the UTAUT model (see Figure 2). The impact of extrinsic motivation is grounded in other contexts (Camera et al.,2016; Sun et al.,2019).



Extrinsic Motivation and External Rewards

Extrinsic motivation refers to the performance of a certain activity because it will lead to an external reward (Deci, 1972). Extrinsically motivated behaviors refer to activities that are unlikely to be performed unless there is an extrinsic reason to do so such as monetary rewards or financial incentives (Gillespie, 2016). Extrinsic motivation is proven to be an important predictor in employment, productivity, and performance (Kreps, 1997; Wright, 2007; Becker, 2018).

External rewards serve as positive reinforcers for a desired behavior (Bénabou & Tirole, 2003). Rewards as a motivational factor have been widely studied in the organizational behavior literature, mainly with reference to the Self-Determination Theory (Deci & Ryan, 1985). External rewards are tangible benefits associated with an action (Birk et al., 2016; Roumani et al., 2015), which is considered a powerful type of extrinsic motivation due to its immediate benefit (Akinwumi et al., 2016; Shi et al., 2022). External rewards can provide the necessary motivation for individuals to adopt new tools and systems, specifically when intrinsic motivations are not sufficient (Budu et al., 2019), further, the adoption of technologies is often contingent upon perceived benefits associated, which can be enhanced through effective reward systems (Holl et al., 2013).

Hypotheses: Extrinsic Motivation and E-government Services Adoption

In the domains of the information system, there is also a key influence of extrinsic motivational factors on ICT-based knowledge-sharing in the workplace (Kankanhalli et al., 2005; Papadopoulos et al., 2013; Rode, 2016), additionally, extrinsic motivators are important drivers of using information systems (Malhotra et al., 2008; Wu & Lu,

2013), and strongly associated with the overall information system success (Petter et al., 2013). Petter et al. (2013) identified extrinsic motivation as a strong determinant of system usage, defining it as incentives—such as financial rewards, recognition, or reputation—that are distinct from performance-related benefits. This distinction is crucial in contexts like e-government, where the use of digital services may not directly improve individual performance but instead focuses on user engagement, making external rewards a key independent motivator.

In e-government systems, the goal is to encourage users to engage with digital services, rather than improve personal performance outcomes. External rewards, such as monetary incentives, play a significant role in increasing engagement by providing tangible benefits that encourage users to adopt e-services (Harwood & Garry, 2015; Eisingerich et al., 2019; Hogberg et al., 2019). Studies by Cappa et al. (2018) and others have shown that both intrinsic and extrinsic motivations are essential in driving participation in virtual communities, where external rewards can be particularly effective in increasing user engagement (Boudreau & Lakhani, 2015; Bullinger et al., 2010; Franzoni & Sauermann, 2014).

A key distinction must be made between performance expectancy and external rewards. Performance expectancy refers to the belief that using a system will result in gains in efficiency or job performance (Venkatesh et al., 2003). In contrast, external rewards are tangible benefits tied specifically to the action of using the system, independent of any performance improvements (Birk et al., 2016; Roumani et al., 2015). For instance, Hu et al. (2019) included both concepts in their research model, showing that performance expectancy reflected job performance improvements, while

external rewards acted as direct incentives for system use. Similarly, Adenuga et al. (2017) conceptualized external rewards as a reinforcement factor distinct from performance expectancy, highlighting how users expect to be rewarded for using the system independently of any efficiency gains.

In the context of e-government, the rewards users receive from engaging with digital services, such as financial incentives or exclusive access, are not tied to improving individual performance but rather serve as extrinsic motivators aimed at driving adoption. These rewards are offered specifically to encourage the use of digital channels and effectively motivate behaviors that may not occur otherwise, especially among users who are less concerned with service efficiency.

Providing monetary incentives or waving fees leads to a significant increase in mobile application adoption (Camera et al., 2016; Sun et al., 2019). This distinction is especially relevant in the e-government context, where external rewards are offered not to enhance service performance but to incentivize digital engagement. Such rewards motivate behaviors that would otherwise be less likely to occur, thereby promoting the adoption of e-government services among users who may not be driven solely by improvements in service efficiency or performance outcomes (Krishnamurthy et al., 2014). Unlike performance expectancy, which motivates users based on expected gains in efficiency or service quality, external rewards provide direct, tangible benefits for adopting e-government services. These rewards are independent of service outcomes and are particularly effective in incentivizing disadvantaged groups, such as low-income individuals, who may not be motivated by

the perceived efficiency of the service alone. The existence of such rewards may encourage citizens to adopt e-government services, therefore our first hypothesis is:

H1: External rewards positively influence the adoption of e-government services.

Additionally, extrinsic motivation can have differential effects across different demographic groups (Malhotra et al., 2008). The citizens' demographic characteristics can provide valuable insights into adoption rates, socioeconomic factors such as age, gender, employment, income, and geographic location affect the extent of the digital divide (Okunola et al., 2017). Moreover, these socio-demographic factors may alter how external rewards influence technology adoption, as the needs and incentives of different groups vary. E-government performance and adoption behaviors may differ significantly across social groups based on these factors, particularly age, geographic location, and income (Ma & Zheng, 2018; Van Den Berg et al., 2020).

The rapid diffusion of digital technologies has produced an age-related digital divide in the adoption of technology, where older age groups are lagging the younger (Lam & Lee, 2006; Charness & Boot, 2022; Lei et al., 2023). Citizens of different age groups display different preferences, abilities, and demands for technologies (Crespo Cuaresma & Lutz, 2021), younger citizens are more likely to use e-government services (Ma & Zheng, 2018), while elderly citizens are less likely to use digital technologies (Xu & Tang, 2020). In particular, older citizens may be more motivated by external rewards, such as financial incentives, due to their fixed income or retirement status (Peek et al., 2014; Chan et al., 2023). The combination of economic constraints and the perceived value of financial incentives could make external

rewards more attractive to this group. Therefore, age seniority could have a major impact on the relationship between external rewards and e-government services adoption.

The geographical location is also a major determinant of e-government services adoption. Rural populations face unique challenges compared to their urban counterparts, including limited infrastructure and access to reliable internet (Schleife, 2010; DeStefano et al., 2023). In developing countries like Jordan, the socio-economic divide is further amplified between urban areas with modern infrastructure and rural areas struggling with access to basic services. Rural populations, who may experience greater economic challenges, are likely to respond more positively to external rewards due to the tangible and immediate benefits these incentives offer (Akinwumi et al., 2016; Shi et al., 2022). Therefore, the rural location could have a significant impact on the relationship between external rewards and e-government services adoption, as these incentives could offset some of the barriers to digital adoption in underserved areas.

Finally, household income is a significant determinant of e-government service use (Sipior et al., 2011). Moreover, Jordan is classified as a low-middle-income country with 14% of the population living below the national poverty line (World Bank, 2021), which indicates that the income levels are below the worldwide average, therefore, low-income households could be more motivated to adopt e-government services if the adoption is associated with a tangible external reward to relieve their financial distress.

In summary, external rewards serve as a key motivator across multiple socioeconomically disadvantaged groups, though the effect of these rewards may vary based on specific demographic factors. For elderly individuals, the reward addresses economic limitations tied to fixed incomes. For rural populations, external rewards help offset geographic and infrastructure barriers. For low-income citizens, the financial benefit serves as a direct incentive to engage with e-government services. Thus, we propose the following hypotheses related to the moderation effect of specific socioeconomic variables:

H2a: The positive effect of external rewards on the adoption of e-government services is stronger for individuals in older age groups.

H2b: The positive effect of external rewards on the adoption of e-government services is stronger for individuals in rural locations.

H2c: The positive effect of external rewards on the adoption of e-government services is stronger for low-income individuals.

Having the required digital skill to access e-government services is an important issue, as citizens may not be able to use the e-services due to lack of knowledge. The adoption of digital technologies is conditional on tech-related skills and access, higher educated citizens tend to adopt technology faster (Crespo Cuaresma & Lutz, 2021). E-government platforms can exclude citizens who lack digital experience (Larsson & Skjølsvik, 2021), and digital technologies require new skills and diminish the need for the skills previously acquired (Lember et al., 2019; Firk et al., 2021). For those without IT proficiency, digital technologies may appear intimidating, and the promise

of rewards acts as a motivating factor to overcome perceived challenges. External incentives become instrumental in addressing the learning curve associated with acquiring IT skills, offering immediate benefits that make the adoption process more attractive (Venkatesh et al., 2003). These rewards serve as catalysts for overcoming resistance to change, fostering digital inclusivity by making e-government services accessible to individuals with diverse skill sets (Beer & Nohria, 2000; Warschauer, 2004; Omazić et al., 2011).

Higher-educated citizens are more likely to use e-government services (Ma & Zheng, 2018), and education is a significant determinant of e-government service use (Sipior et al., 2011). Additionally, education is important to the use of computer equipment (Van Dijk, 1999; Van Dijk & Hacker, 2003). Moreover, E-government adoption is adversely affected by the digital divide since the adoption of e-government requires education and training to develop the required computer knowledge and skills (Zhao et al., 2018), additionally, citizens who engage with the e-government tend to be higher income and higher educational groups (Thomas & Streib, 2003).

Despite the fact that the adoption of modern technology has grown rapidly in developing countries, a challenge remains in the digital skills imbalance and the poor education outcomes, many individuals and households in disadvantaged communities have low education levels and trapped in low-paid work with little or no access to social protection (Kaplinsky & Kraemer-Mbula, 2022), disadvantaged groups may require financial assistance to afford the digital skills and education, consequently, the

existence of external rewards could encourage those groups to adopt e-government services. Therefore, we hypothesize the following:

H3a: The positive effect of external rewards on the adoption of e-government services is stronger for individuals with lower educational levels.

H3b: The positive effect of external rewards on the adoption of e-government services is stronger for individuals with no digital skills.

Methodology

Context: Digital Transformation in the Government of Jordan

Jordan is a lower-middle-income country in West Asia with a population of around 10 million people. Most of the population lives in the capital, Amman, and the country faces a significant socio-economic divide (World Bank, 2023). While the nation has made progress in modernization and economic diversification, disparities persist. The influx of refugees from neighboring conflict zones has further strained resources and deepened the socio-economic imbalance (World Bank, 2023).

Jordan's context differs significantly from developed economies due to its unique combination of infrastructure limitations, socio-economic disparities, and regional instability. Unlike developed nations, where internet access, reliable electricity, and digital literacy are widespread, Jordan faces major gaps in digital infrastructure, particularly in rural areas. As a lower-middle-income country, these challenges are worsened by the fact that many—especially in low-income and rural areas—lack access to digital devices and the skills needed to use e-government services.

Moreover, the government's resources are strained by ongoing economic challenges

and the influx of refugees, further complicating efforts to implement and maintain large-scale digital initiatives. These factors, combined with the socio-economic divide, make Jordan's path to digital transformation fundamentally different from more developed countries, where resources and infrastructure are more stable and accessible.

The digital transformation in the public sector in Jordan is led by the Ministry of Digital Economy and Entrepreneurship (MODEE). The country's Digital Transformation Strategy was launched in 2020 in line with Jordan Vision 2025. The strategy outlines the changes and strategic requirements to improve the delivery of public services, enhance the efficiency of government performance, meet the needs of beneficiaries, and enhance e-participation levels, improve the quality of life more effectively, sustainably, and reliably, and achieve well-being.

The improvement of e-government services by the Jordanian government involved providing six different access methods to e-services which are: (1) government entity websites, where the citizen can register through creating a user name and password then use the electronic services through the website, (2) government entities mobile application where there is 40 government entities have its own mobile applications, and citizens' or corporations can access and request services, (3) e-government website, which serves as a web-based gateway for the services, (4) e-government mobile application (Sanad), (5) electronic booths, available inside government agencies and other post offices to get the services electronically instead waiting in the queue to get the service in person, and (6) knowledge stations which are computer labs

that allow citizens to use the computers to access the e-government services and online learning, mainly in the rural areas far from the government agencies offices.

Data

To test our hypotheses, we used data from Jordan's Technology and Internet Survey for the year 2021. The dataset includes the responses to a questionnaire prepared by the Ministry of Digital Economy and Entrepreneurship in Jordan (see Appendix 2)². The purpose of the survey was to identify the spread of technology and the Internet across Jordan, in addition to the use of technology to access e-government services through different means such as websites, mobile applications, electronic booths, and knowledge stations. The data was collected in the fourth quarter of 2021 by a team of researchers from the Ministry and the Jordanian Department of Statistics. The data collection team included field officers, researchers, supervisors, and data quality auditors³. The researchers visited the households and collected the data directly from everyone in the household. The dataset included 10,703 individuals over 16 years of age.

Measures

We measure our dependent variable e-government service adoption with a binary variable. The variable reflects whether the citizen used any of the six methods available to access e-government services: (1) government entity websites, (2) government entities mobile applications, (3) e-government website, (4) e-government

² Details about the sampling process and data collection, can be found on the Jordanian government's official website: <https://www.modee.gov.jo>

³ Citizens were obliged to answer all the survey questions.

mobile application (Sanad), (5) electronic booths, and (6) knowledge stations. The variable is equal to one if the individual used any of the e-government and zero otherwise.

To investigate the impact of extrinsic motivation on e-government service adoption, we operationalized the independent variable external reward as a binary construct within our analysis. This variable is coded as 1 for citizens who are eligible to receive various forms of government aid and assistance. These include benefits such as lower fares on airline tickets, access to health insurance, customs exemptions, waiver of work permit fees, as well as support for training, education, and employment.

We further explore the impact of socioeconomic variables and digital skills on e-government services adoption and how these variables moderate the effect of external reward on the adoption. To capture the full complexity of these relationships, we included both linear and quadratic terms for key demographic variables such as age, income, and education in our regression models. This approach allows us to capture diminishing or increasing returns, providing a more nuanced understanding of the moderating effects of these variables. Prior studies have also demonstrated the importance of modelling non-linear effects to better assess the role of demographic characteristics in technology acceptance (Morris & Venkatesh, 2000; Sun & Zhang, 2006).

The first group, the socio-economic conditions, includes age, low income, and rural location. The age variable is continuous, the sample age ranges between 16 and 97, and we also used the quadratic term of the age to explore non-linearities. We

generated a binary variable to indicate whether the citizen lives within a low-income family which is lowest 14% of the income distribution (World Bank, 2021), finally, we used a binary variable for the location to indicate whether the individual is located in a rural area. The second group of variables includes the digital skills and literacy: lack of IT skills and number of years in education. We created a binary variable to indicate whether an individual lacks the digital skills required for using e-services, particularly in relation to e-payments and e-commerce. This variable is coded as 1 for individuals who do not engage in online activities such as e-commerce, e-banking, mobile wallets, or other internet payment methods (e.g., Google Pay, PayPal). Additionally, we used the number of years in education to identify the education level of the citizen, the years of education of less than 13 years indicates that the citizen has only attended primary and high school education, and equal or greater than 13 indicates that the student attended higher education in terms of Bachelor, master's, or PhD degrees. We also used the quadratic term of education for non-linearities. A full description of the relevant variables is included in Table 1.

Model

Due to the binary nature of our dependent variable, e-government services adoption, we employ logit regressions. We present different specifications. The first specification (Column 1 on Table 1) includes the variables of control, namely, the socio-economic conditions (age, low income, and rural location) and the digital skills and literacy (Lack IT Skills and Education Years). Column 2 builds on specification one and includes our main independent variable of interest, external reward (Hypotheses 1). Columns 3 to 7 include the interaction terms of external reward with

the different socioeconomic and digital skills. Column 3 shows the interaction of external reward, age, and age squared (Hypotheses 2a), column 4 shows the interaction of external reward and rural location (Hypotheses 2b), column 5 shows the interaction of external reward and low income (Hypotheses 2c), column 6 shows the interaction of external reward, education, and education squared (Hypotheses 3a), and column 7 show the interaction of external reward and lack of IT skills (Hypotheses 3b).

Results

Descriptive statistics

The results were analyzed using Stata 18. Table 2 presents descriptive statistics for the variables included in the analysis. The mean, standard deviation, minimum, and maximum values. The sample age ranged between 16 and 97, and the average age was 39 years, 39% of the sample live in rural areas, the years in education ranged from 0 to 23 years, with an average of 9 years. The low-income households accounted for 14% of the sample, and 16% of the sample are eligible for external reward. Moreover, 54% of the respondents adopted the e-government services using different methods; 41% used the Sanad mobile application, 21% used the government entity website, 17% used the e-government website, 14% used the government entity application, and less than 1% used the electronic booths and knowledge stations. Additionally, in terms of technology equipment, the smartphone is the most popular with 24% of respondents using it, followed by the laptop with 12% of the respondents, then personal computers with 10% of the respondents.

Regression results

Table 3 shows the logit regression results. The first model indicates the impact of the control variables on the dependent variable, The age had a positive and significant impact on adoption $\beta = 0.037$ ($p < 0.01$) and the quadratic term of age had a negative and significant impact on adoption $\beta = -0.001$ ($p < 0.05$) (with a turning point of 106 years), indicating a positive but decreasing impact of age on adoption of e-government. the education years had a negative and significant impact on adoption $\beta = -0.276$ ($p < 0.01$) and the quadratic term of age had a positive and significant impact on adoption $\beta = 0.016$ ($p < 0.01$), which indicates that the likelihood of adoption decrease till it reaches a turning point of 8 years of education then it will increase, only 20% of the sample are on the left side of the curve and the remaining 80% on the positive increasing side. The rural location had a negative and significant impact on the adoption $\beta = -0.341$ ($p < 0.01$), the lack of IT skills had a negative and significant impact on the adoption $\beta = -0.926$ ($p < 0.01$), the low income did not have a significant impact. Among the technology equipment both the personal computer and laptop had a significant and positive impact $\beta = 0.483$ ($p < 0.01$) and $\beta = 0.734$ ($p < 0.01$) respectively, and the smartphone had a negative and significant impact $\beta = -0.488$ ($p < 0.01$) and the tablet did not have a significant impact.

The second model shows the impact of the explanatory variable the external rewards on e-government service adoption, the relationship is both significant and positive $\beta = 0.438$ ($p < 0.01$), which supports hypothesis 1, The marginal effect

suggests that the likelihood of e-government services adoption increases by 0.109 for the external reward, which corresponds to a 20 % increase at the sample mean.⁴

Models 3 to 7 explore the moderating impact of the socio-economic conditions and digital skills. In column 3, The analysis revealed a significant negative interaction between the age and external rewards $\beta = -0.203$ ($p < 0.01$) and significant positive interaction between the quadratic term of age and external rewards $\beta = 0.002$ ($p < 0.01$). Figure 1 in Appendix 1 shows the curvilinear relationship between the impact of the interaction of age and external rewards on e-government services adoption. Figure 1 shows that the effect of external reward is particularly notable from 60 years of age, supporting hypothesis 1a. In column 4, the interaction between the rural location and external rewards is significant, and positive $\beta = 0.643$ ($p < 0.01$), which supports hypothesis 2b. Figure 2 in Appendix 1 shows that external rewards are particularly relevant in the context of rural areas, where there is a significant difference in the probability of adoption between those receiving the external reward and those who do not.

In column 5, the interaction between the low-income and external rewards is significant and positive $\beta = 0.856$ ($p < 0.01$), which supports hypothesis 2c. Figure 3 in the Appendix 1 shows external rewards are particularly relevant for low-income households, where there is a significant difference in the probability of adoption depending on receiving the external reward. Column 5 revealed a significant negative

⁴ The marginal effect of 0.109 for external rewards was calculated using a post-estimation margins command after conducting a logit regression. This value represents the change in the probability of adopting e-government services when a citizen qualifies for external rewards, while holding other variables at their means. The 20% increase was derived by dividing the marginal effect (0.109) by the sample mean of e-government adoption (0.539, as shown in Table 2). This indicates that qualifying for external rewards increases the likelihood of adoption by approximately 20% relative to the overall adoption rate of 53.9% in the sample.

interaction between education and external rewards $\beta = -.201$ ($p < 0.01$) and a significant positive interaction between the quadratic term of education and external rewards $\beta = 0.005$ ($p < 0.1$). Figure 4 in Appendix 1 shows the impact of the interaction of education and external rewards on e-government services adoption. The impact of external rewards is significant for those groups with lower levels of education, supporting hypothesis 3a. Finally, in column 6, the lack of IT skills had a positive and significant interaction with the external reward $\beta = 1.075$ ($p < 0.05$), which support hypothesis 3b. Figure 5 in Appendix 1 shows that external rewards are particularly relevant in the absence of digital skills. Robustness check and further results are included in Appendix 1.

Discussion

The findings of this study highlight the critical role that extrinsic motivation plays in shaping the landscape of e-government adoption. Our results, which support hypothesis 1, confirm that external rewards significantly and positively influence citizens' likelihood of embracing e-government services. This aligns with established theories in organizational behavior, particularly in the realm of Self-Determination Theory, where external incentives serve as potent drivers for desired behaviors (Bénabou & Tirole, 2003). The implications of this result extend beyond the immediate context of e-government adoption, echoing the broader literature on technology acceptance. Kankanhalli et al. (2005), Papadopoulos et al. (2013), and Rode (2016) have all emphasized the pivotal role of extrinsic motivational factors in fostering ICT-based knowledge-sharing and overall information system success. For instance, our results support previous works that identified the role extrinsic

motivation plays in the success of information system adoption (Kankanhalli et al., 2005; Papadopoulos et al., 2013; Rode, 2016; Malhotra et al., 2008; Wu & Lu, 2013) and mobile applications adoption (Camera et al., 2016; Sun et al., 2019). This work also validates the impact of socioeconomic conditions such as age, low income, and rural location on e-government service adoption.

Our results support previous literature on age-related digital divides by showing that different age groups exhibit distinct preferences, abilities, and demands for technologies (Crespo et al., 2021). Our results support previous studies highlighting the impact of age on technology adoption and use (Lam & Lee, 2006; Charness & Boot, 2022; Lei et al., 2023). Our results also reveal that younger citizens, when receiving external rewards, exhibited a lower likelihood of embracing e-government services. However, this trend reverses as citizens approach the age of 43, at which point the likelihood of adoption begins to increase, supporting hypothesis 2a. This could be attributed to the fact that by this age most of the citizens would have completed 20 years of work and are subject to voluntary retirement and receiving a pension.

Furthermore, the urban-rural divide emerges as a crucial factor influencing e-government adoption in the presence of external rewards. Our results found that citizens in rural areas may exhibit a positive response to external rewards in the context of e-government adoption, supporting our hypothesis 2b. This can be explained by economic conditions of rural areas, where citizens often face lower average incomes and limited employment opportunities, making external rewards, such as financial incentives, particularly appealing and effective motivators (Addo,

2021). Limited access to resources, including educational opportunities and technological infrastructure, further enhances the significance of external rewards, acting as catalysts to overcome barriers associated with resource constraints (Sipior et al., 2011). In addressing digital inclusive challenges, where rural populations may have lower levels of digital literacy, external rewards provide additional incentives for individuals to embrace technology use (Crespo et al., 2021).

Moreover, the interaction between external rewards and low-income unveils a significant positive relationship, supporting hypothesis 2c and indicating that citizens within economically disadvantaged groups are more likely to adopt e-government services when motivated by external rewards. This finding aligns with existing literature emphasizing the household's significant role in determining e-government service use (Sipior et al., 2011). In a country like Jordan, where income levels are below the global average, the economic benefits associated with external rewards can be particularly compelling.

We also find a positive effect of external rewards on the adoption of e-government services would be stronger for individuals with lower educational levels, supporting hypothesis 3a. The empirical results reveal that the moderation impact of education is indeed significant. Citizens with lower educational levels exhibit a stronger positive response to external rewards, suggesting that educational disparities play a crucial role in shaping the dynamics of e-government adoption.

Our analysis also revealed a significant moderation effect of digital skills on the relationship between external rewards and e-government adoption., supporting hypothesis 3b. Citizens lacking digital skills demonstrate a heightened positive

response to external rewards, indicating that the presence of rewards acts as a crucial motivational factor for overcoming the perceived challenges associated with digital technologies. This finding aligns with the broader literature on digital inclusion, where external incentives are recognized as catalysts for overcoming resistance to change and fostering inclusivity (Beer & Nohria, 2000; Warschauer, 2004; Omazić et al., 2011).

Conclusion

This paper provided empirical evidence on the impact of external rewards on e-government service adoption in Jordan, employing a large-scale dataset from Jordan's 2021 Technology and Internet Survey, extending the original UTAUT model to include external rewards as an extrinsic motivator, the research deepens our understanding of how such incentives can drive adoption. The data were analyzed using logit regression, and the analysis validated the impact of the external reward on e-government service adoption moderated by socio-economic conditions, digital skills, and literacy. In particular, our study sheds light on how disadvantaged groups such as senior citizens, citizens living in rural areas, and those who are categorized as low-income households tend to adapt e-government services if the service was associated with an external reward.

This research makes several significant theoretical contributions to the literature on e-government services adoption. First, the research addresses the context of a developing country facing unique socio-economic challenges and addresses the unfortunate side of the divide, where the majority of literature addressed the e-government adoption in the Western context, this research helps in addressing this

imbalance and provides more insights of the developing countries digital transformation challenges and possible solutions to bridge the digital divide, adding to the e-government literature in developing countries (Ramirez-Madrid et al., 2022; Addo, 2021). By examining how external rewards can drive digital engagement, particularly among disadvantaged groups, the study highlights strategies that could help bridge the digital divide in developing economies. Second, it addressed the demand side of e-government by focusing on the factors driving citizens' adoption of e-government services, since the supply of e-government services will not contribute to the digital transformation goals without adequate adoption by citizens, understanding what drives and sustains adoption, which also adds to the literature that addressed different aspects of the demand side such as trust (Chan et al., 2010; Porumbescu, 2016) and privacy concerns (Willems et al., 2022). Third, the research extended the UTAUT model to include external rewards as an extrinsic motivation factor. While previous research has largely focused on performance expectancy and social influence as drivers of technology adoption, external rewards introduce a new dimension of motivation by providing direct and tangible incentives for using e-government services. These findings are particularly relevant in the context of developing countries, where financial incentives may have a greater impact on adoption decisions than perceived efficiency or social influence. This is a novel contribution that builds on calls to expand the UTAUT model by including new predictors (Blut et al., 2021). Finally, it contributes to the e-government literature with large-scale empirical evidence, testing the cause-and-effect relationship between

variables providing more generalizable results about the population, and answering the calls for more quantitative research in digital transformation.

Our paper provides several lessons for policy makers, particularly in developing economies, looking to increase the level of adoption of the e-government services. Though the government of Jordan has progressed in its digital transformation, a challenge remains in the low adoption rates. Our research has highlighted critical factors that play important roles in shaping the citizens' adoption of e-government services, particularly the role of external rewards in motivation adoption among disadvantaged populations. Based on our findings, we propose a set of policy implications to promote digital inclusion and enhance e-government adoption among citizens. First, the government should leverage external rewards to encourage citizens to adopt e-government services. These rewards can act as motivators, encouraging citizens—especially those from disadvantaged backgrounds—to engage with e-government services. However, it is important to note that while social programs themselves are not designed to drive e-government adoption, when offered through digital channels, they provide a tangible incentive for citizens to transition to e-government services. Second, establish a mechanism for technology grants or subsidies for low-income households to enable them to acquire essential equipment, such as computers, laptops, and smartphones, which can reduce economic barriers and facilitate broader access. Third, establish digital inclusion curricula and implement comprehensive digital literacy and upskilling training programs, targeting disadvantaged communities in specific areas. Finally, governments shall focus their efforts on mobile-centric applications, which in turn can help governments achieve

their cost efficiency and resource optimization goals. By implementing those policies, governments can take a step toward fostering digital inclusion and ensuring that e-government services are accessible to different segments of society.

While this research provides valuable insights into the relationships between external rewards and e-government services adoption in Jordan, several limitations require consideration. First, the cross-sectional nature of this research limits analyzing the changes in responses or behaviors over time. A longitudinal approach may offer a deeper understanding of how these variables evolve over time, allowing for the identification of trends and changes. Second, while the analysis demonstrated that external rewards significantly impact the number of access methods adopted, it did not directly control the frequency of service use, as this information is not available in the survey. This presents a limitation in disentangling whether citizens engage more with e-government services primarily due to external rewards or out of necessity (e.g., needing to access government aid). Third, the scope of extrinsic motivation in this study was limited to external economic rewards, such as monetary incentives, and did not explore other forms of rewards, such as non-economic incentives (e.g., awards, points, or recognition). Future studies could examine a broader range of extrinsic motivators to see how different incentives influence e-government adoption. Fourth, future research could split the sample based on specific social programs (e.g., elderly pensions, disability benefits) to analyze how different types of government aid might affect e-government adoption differently. Fifth, the geographical scope of the research is focused on Jordan a country with specific socio-economic challenges and may not be generalizable for countries with different socio-economic profiles.

Comparative studies across diverse contexts could provide insights into how socio-economic conditions influence the effectiveness of external rewards in different regions. Finally, future research could use primary data to have more detailed data directly from the citizens.

Tables

Table 1: Variables Description

Variable Name	Description	Type	Possible Values	Basis of Calculation
Adoption	E-Government services adoption regardless of the method of accessing the services	Binary variable	Yes, No	Respondents answer to any of the questions related to the adoption of e-government channels.
Entity App	Accessing e-government services through the governmental organization mobile application	Binary variable	Yes, No	Respondents answer to the question related to the use of e-government services through the government entity mobile application.
Entity Website	Accessing e-government services through the governmental organization website	Binary variable	Yes, No	Respondents answer to the question related to the use of e-government services through the government organization website.
Sanad App	Accessing e-government services through the e-government mobile application "Sanad"	Binary variable	Yes, No	Respondents answer to the question related to the use of e-government services through Sanad Application
E-Government Website	Accessing e-government services through the e-government website	Binary variable	Yes, No	Respondents answer to the question related to the use of e-government services through the the e-government website
Electronic Booths	Accessing e-government services through the government-provided electronic booths	Binary variable	Yes, No	Respondents answer to the question related to the use of e-government services through the electronic booths.
Knowledge Stations	Accessing e-government services through the government-provided Knowledge Stations	Binary variable	Yes, No	Respondents answer to the question related to the use of e-government services through the Knowledge Stations.

Variable Name	Description	Type	Possible Values	Basis of Calculation
Number of adoption methods	The total number of e-government services access methods adopted by an individual	Count variable	0,1,2,3,4,5,6	The number of (Yes) responses related to the adoption of services through the six e-government channels.
Age	Individual age	Continuous Variable	Values range between 16 and 97	Directly from the survey responses.
Rural	It indicates whether the individual lives in rural area	Binary	Yes, No	Calculated by grouping the governorates to urban/ rural
Education Years	The number of years of education an individual obtained in school and higher education	Continuous	Values range between 0 and 23	Calculated by identifying the years in education for each education level starting from school till postgraduate degree
External Reward	Whether an individual is eligible to receive aid from government for being eligible for pension or has a disability	Binary	Yes, No	Calculated by identifying whether the individual is eligible for aid
Lack IT Skills	Whether the individual does not have the skills to use the e-payments and e-commerce	Binary	Yes, No	Calculated by identifying the participants who used the internet for the e-commerce or e-payments; including e-banking, mobile wallets, or other internet payment methods
Low income	Households with income within the lowest 14% of the income distribution	Binary	Yes, No	Calculated by identifying if the household income is in the lowest 14%
Gender	Male/ Female	Binary	Yes, No	Directly from the survey
Personal Computer	Whether the individual has a personal computer	Binary	Yes, No	Calculated from the respondents' answers to the question related to the type of computing equipment used.
Laptop	Whether the individual has a laptop	Binary	Yes, No	Calculated from the respondents' answers to the question related to

Variable Name	Description	Type	Possible Values	Basis of Calculation
				the type of computing equipment used.
Tablet	Whether the individual has a tablet	Binary	Yes, No	Calculated from the respondents' answers to the question related to the type of computing equipment used.
Smartphone	Whether the individual has a smartphone	Binary	Yes, No	Calculated from the respondents answer related to not using the computer due to having a smartphone.

Table 2: Descriptive Statistics

Variable	Mean	SD	p25	p75	Min	Max
Age	39.048	17.231	24	51	16	97
Age ²	1821.646	1553.509	576	2601	256	9409
Gender	0.497	0.500	0	1	0	1
Rural	0.390	0.488	0	1	0	1
Education Years	9.805	4.611	8	12	0	23
Education Years ²	117.389	83.796	64	144	0	529
Low Income	0.140	0.347	0	0	0	1
External Reward	0.159	0.366	0	0	0	1
Lack IT Skills	0.977	0.149	1	1	0	1
Entity Website	0.213	0.409	0	0	0	1
Entity App	0.138	0.345	0	0	0	1
E-government Website	0.170	0.376	0	0	0	1
Sanad App	0.409	0.492	0	1	0	1
Electronic Booths	0.008	0.089	0	0	0	1
Knowledge Stations	0.009	0.093	0	0	0	1
Adoption	0.539	0.499	0	1	0	1
Number of Adoption Methods	0.946	1.337	0	1	0	6
Gender	0.497	0.500	0	1	0	1

PC	0.102	0.303	0	0	0	1
laptop	0.129	0.335	0	0	0	1
tablet	0.013	0.112	0	0	0	1
smartphone	0.240	0.427	0	0	0	1

Table 3: Logit Regression – Adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.037*** (0.006)	0.051*** (0.007)	0.132*** (0.012)	0.049*** (0.007)	0.048*** (0.007)	0.063*** (0.007)	0.051*** (0.007)
Age ²	-0.001** (0.000)	-0.000*** (0.000)	-0.002*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)
Gender	-0.713*** (0.044)	-0.707*** (0.044)	-0.696*** (0.044)	-0.704*** (0.044)	-0.702*** (0.044)	-0.739*** (0.044)	-0.706*** (0.044)
Education Years	-0.276*** (0.017)	-0.268*** (0.018)	-0.246*** (0.018)	-0.262*** (0.018)	-0.264*** (0.018)	-0.185*** (0.020)	-0.267*** (0.018)
Education Years ²	0.016*** (0.001)	0.016*** (0.001)	0.015*** (0.001)	0.016*** (0.001)	0.016*** (0.001)	0.013*** (0.001)	0.016*** (0.001)
Rural	-0.341*** (0.044)	-0.340*** (0.044)	-0.345*** (0.044)	-0.420*** (0.047)	-0.342*** (0.044)	-0.363*** (0.044)	-0.340*** (0.044)
Lack IT Skills	-0.926*** (0.197)	-0.917*** (0.197)	-0.911*** (0.196)	-0.912*** (0.196)	-0.917*** (0.196)	-0.932*** (0.195)	-1.023*** (0.210)
Low Income	-0.031 (0.061)	-0.031 (0.061)	-0.002 (0.061)	-0.033 (0.061)	-0.136** (0.067)	-0.009 (0.062)	-0.031 (0.061)
Personal Computer	0.483*** (0.075)	0.496*** (0.075)	0.568*** (0.076)	0.488*** (0.075)	0.490*** (0.075)	0.473*** (0.075)	0.496*** (0.075)
Laptop	0.734*** (0.075)	0.743*** (0.075)	0.803*** (0.076)	0.738*** (0.075)	0.732*** (0.075)	0.725*** (0.074)	0.742*** (0.075)
Tablet	0.045 (0.203)	0.037 (0.204)	0.039 (0.210)	0.039 (0.204)	0.028 (0.204)	0.043 (0.203)	0.036 (0.204)
Smartphone	-0.488***	-0.481***	-0.471***	-0.481***	-0.485***	-0.476***	-0.480***

	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
External Reward		0.438*** (0.102)	4.570*** (0.787)	0.214* (0.110)	0.301*** (0.106)	1.622*** (0.186)	-0.622 (0.546)
External Reward#Age			-0.203*** (0.029)				
External Reward#Age ²			0.002*** (0.000)				
External Reward#Rural				0.643*** (0.131)			
External Reward#Low Income					0.856*** (0.198)		
External Reward#Education Years						-0.201*** (0.043)	
External Reward#Education Years ²						0.005* (0.003)	
External Reward#Lack IT Skills							1.075** (0.546)
_cons	1.211*** (0.249)	0.961*** (0.254)	-0.391 (0.305)	0.980*** (0.254)	1.002*** (0.254)	0.293 (0.268)	1.055*** (0.265)
<i>N</i>	10703	10703	10703	10703	10703	10703	10703
Log likelihood	-6568.549	-6559.121	-6519.679	-6547.045	-6548.942	-6509.091	-6557.614
Pseudo R-sq.	0.111	0.112	0.117	0.114	0.113	0.119	0.112

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

Exploring Citizen Sentiment Toward M-Government: The Role of Media Framing, Mandatory Adoption, and App Development

Abstract

This paper explores how media framing, mandatory adoption and application development shape the public sentiment towards m-government services. Using sentiment analysis, topic modeling, regression analysis, and fsQCA, we analyze 10,725 user reviews and media announcements related to an m-government application. Findings reveal that early adoption was marked by negative sentiment due to usability issues, but public perception improved with updates. However, mandatory adoption negatively impacted sentiment, reinforcing prior studies on resistance to imposed digital services. Media framing played a crucial role, with positive coverage boosting sentiment and negative framing amplifying distrust. This study contributes to m-government and media framing literature, highlighting the need for continuous usability improvements, strategic media engagement, and voluntary adoption strategies.

Keywords: M-government, Citizen Sentiment, Media Framing, Mandatory Adoption, Sentiment Analysis, Topic Modeling, Mobile Application, E-government,

Introduction

The rapid advances in wireless and mobile communications technologies have transformed the way governments provide services to citizens. The rise of Mobile

Government (m-government), a subset of electronic government (e-government), has allowed public services to be delivered more efficiently and cost-effectively through mobile applications (Al-Hujran, 2012). Unlike traditional e-government platforms that rely on web-based access, m-government offers greater accessibility and convenience, enabling citizens to interact with government services anytime and anywhere (Mossey et al., 2019; Sharma et al., 2018).

Despite these advancements, the success of m-government applications is highly dependent on citizen adoption and satisfaction, which are influenced by multiple factors, including ease of use, functionality, perceived trust, and government communication strategies (Wirtz et al., 2021; Almarashdeh & Alsmadi, 2017). Many initiatives struggle with user dissatisfaction, technical challenges, and public resistance to adoption (Mossey et al., 2019). One major obstacle is the lack of a citizen-centric approach in m-government service design, as governments often prioritize technological development over understanding the needs and expectations of users (Kowalski et al., 2020). Without integrating citizen feedback, government-led digital services may fail to achieve widespread acceptance and positive public engagement. Sentiment analysis is one of the valuable tools that help in identifying citizens' perceptions and expectations from the government (Verma, 2022; Troisi et al., 2022), and allows government officials to leverage this information to improve services and communication with the citizens (Kavanaugh et al., 2012).

In parallel, media plays a crucial role in shaping public perceptions of government initiatives (Sembor, 1993). Studies in public administration and political science have extensively documented how media framing influences public opinion, trust in

government, and policy acceptance (Margetts, 2018; Boulianne, 2020). Media coverage, particularly through official government announcements and news reports, can frame digital services in a way that encourages or discourages adoption (Gilardi et al., 2022). While research on media framing and public opinion has gained traction in various domains, including foreign policy, tourism, and elections (Baum & Potter, 2008; Hao et al., 2020; Kalla & Broockman, 2018), its application to m-government services remains underexplored. Understanding how media narratives influence public sentiment toward m-government platforms is critical, as governments increasingly rely on digital services to engage with citizens.

The existing literature on m-government focuses adoption intentions (Shareef et al., 2016; Wirtz et al., 2021), accessibility (Liu et al., 2014), influencing factors (Faisal & Talib, 2016), and service quality (Al-Hubaishi et al., 2017). While valuable, these studies do not fully capture the broader societal, contextual and behavioral factors that influence citizen sentiment toward m-government applications. With the rise of social media and user-generated data, citizens now express their opinions dynamically through online platforms, including mobile app reviews, providing a rich and underutilized source of public sentiment data. However, few studies have leveraged large-scale sentiment analysis and topic modeling to examine public discourse surrounding m-government applications.

Additionally, research on mandatory technology adoption in public services has highlighted concerns regarding user resistance and lack of trust when governments impose digital platforms without voluntary adoption (Alkraihi, 2020). While some

governments enforce the use of m-government applications, the impact of such policies on the evolution of public sentiment over time remains insufficiently studied.

This paper addresses several these gaps in the literature by integrating insights from public opinion research, media framing theory, and sentiment analysis to examine the evolution of citizen sentiment toward m-government services. Unlike previous studies that focus primarily on adoption factors, this research explores the intersection of government actions, media narratives, and user experiences to uncover how these elements collectively shape public perceptions.

The case of Jordan's Sanad application, a government-developed mobile platform launched in 2020 for digital services, provides a compelling example of how mandated adoption, media discourse, and evolving app functionalities shape public sentiment over time. The study leverages a novel data-driven approach, analyzing over 10,000 user reviews from the Google Play Store for the Sanad application for the period 2020-2023, along with media reports and government announcements, to provide a comprehensive, real-time understanding of public sentiment. To achieve this, the study employs a combination of sentiment analysis, topic modeling, regression analysis, and fuzzy-set qualitative comparative analysis (fsQCA). These methods allow for a deeper investigation into the patterns, drivers, and consequences of public sentiment, moving beyond conventional survey-based approaches.

This research aims to answer two fundamental questions:

- 1) What are the key themes and sentiments expressed in citizen opinion presented in the reviews of the m-government application and how does the citizens' sentiment evolve through various stages of the application development?

- 2) How do different actions by policymakers shape public opinion, including newspaper announcements, mandating the use of the app, and the evolution of the app through various stages?

Our findings show that citizen sentiment toward the m-government application evolved across different development stages. The initial phase of mandatory adoption triggered predominantly negative sentiment due to technical issues and usability concerns.

However, sentiment improved as new features and updates enhanced functionality and accessibility. Media framing also played a role, with positive government announcements boosting approval, while discussions on mandatory use led to more polarized responses. Topic modeling revealed persistent concerns about technical performance, accessibility, and government communication. Our findings emphasize the need for citizen feedback, positive communication, and user-centric design to ensure successful m-government adoption.

This research contributes to both theory and practice. From a theoretical perspective, this study extends media framing theory by applying it to the domain of digital government services, demonstrating how government announcements and news framing impact public attitudes toward technology adoption. Additionally, it advances research on citizen sentiment analysis in public service management by showcasing the potential of computational techniques to extract meaningful insights from large-scale user-generated data, in response to calls for more research related to the citizens' perception of public services (Hvidman, 2019). Despite the appealing citizen-centric ambitions for governments, they are often forgotten, and the citizens' needs are not fulfilled in practice (Axelsson et al., 2010). From a practical standpoint, the study offers actionable

recommendations for policymakers and digital service designers to improve m-government adoption, user experience, and citizen engagement.

M-Government

The emergence of information and communication technology led governments to adopt modern digital solutions to deliver services to their citizens. These services can be delivered through the internet using web technology (e-government), but the widespread adoption of mobile technologies has enabled a shift toward m-government (Abu-Shanab & Abu-Tair, 2014). The transition from e-government to m-government is driven by the increasing capabilities and accessibility of mobile devices (Sheng & Trimi, 2008; Abaza & Saif, 2015). M-government is a sub-set of e-government and refers to the government's use of mobile and wireless technology to deliver its services (Chen et al., 2016). Unlike traditional e-government platforms, m-government services can reach citizens in remote areas using mobile internet and pre-installed applications (Liu et al., 2014). M-Government reflects the applications of mobile devices in the public administration context (Wirtz et al., 2021). Additionally, it extends e-government applications to mobile and wireless channels (Sheng & Trimi, 2008).

M- government services have a number of distinct features including affordability, reachability, ubiquity, timely information delivery, low digital literacy requirement, personalized information delivery, and emergency management capabilities (Liu et al., 2014). Beyond these benefits, the m-government enhances the scope of delivery of government services, both geographically and in terms of the number of people regardless of the wired technology infrastructure, increases the efficiency and effectiveness of government employees, and facilitates better citizen participation in

decision making (Sheng & Trimi, 2008; (Abu-Shanab & Abu-Tair, 2014). Due to the advancements in mobile technology and the demand for more responsive government services, public organizations all over the world are seeking to leverage mobile technologies to provide services to citizens (Sheng & Trimi, 2008). M-government emerged with the recent advancements of the network's infrastructure and mobile computing techniques (Al-Hujran, 2012) and makes a technology-driven government service more mobile, dynamic, accessible, and available (Shareef et al., 2016). However, successful m-government implementation requires governments to carefully monitor and analyze end-users' wants and their perceived benefit from using m-government applications (Sheng & Trimi, 2008).

M-government solves the challenges associated with the traditional e-government, particularly in developing economies where the high implementation and infrastructure costs, limited access to computer equipment, high Internet fees, as well as low digital literacy have hindered digital service adoption (Liu et al., 2014). In many of these regions, the rapid growth of mobile phone usage has provided a cost-effective alternative to conventional e-government platforms (Liu et al., 2014). This shift has led to the concept of "technology leapfrogging," where developing countries bypass earlier technological stages and adopt more advanced solutions directly (Davison et al., 2000). Leapfrogging allows developing countries such as Jordan to achieve advanced state of information and communications technology connectivity rapidly without following the traditional phased development of digital infrastructure (Ng & Tan, 2018; Tan et al., 2018).

Furthermore, m-government is suitable to extend the benefits of e-government to remote regions and developing countries characterized by the digital divide, which remains a key

problem as digitalization initiatives continue to advance, leaving some citizens behind and limiting certain population groups from accessing personal computers and internet connectivity (Mossey et al., 2019). However, the population in remote areas, particularly developing countries are facing major expansion in mobile services as compared to land telecommunications (Shareef et al., 2012). Mobile devices and smartphones provide an alternative means to utilize technology to access information, services, and social media without the need for private or public internet connectivity through broadband wireless connection and at a lower cost (Mossey et al., 2019). Therefore, the use of m-government can support bridging the digital divide, as mobile services seek to address concerns related to the accessibility resulting from socioeconomic factors such as income, education level, gender, age, disability, language proficiency, and regional discrepancies (Mossey et al., 2019).

Research on m-government has examined a range of topics, including citizens' usage intentions (Wirtz et al., 2021), citizens' access to and perceptions of m-government services (Liu et al., 2014), the cultural influences shaping attitudes toward m-government adoption (Shareef et al., 2016), factors influencing m-government initiatives (Faisal & Talib, 2016), and service quality evaluation (Al-Hubaishi et al., 2017). Scholars have explored m-government across various geographic contexts and research methodologies. For instance, Liu et al. (2014) investigated the adoption of mobile government by rural populations in China using a sample of 409 families and examined the interdependences among rural inhabitants' demographic attributes, access to and perceptions of mobile government. Similarly, Abaza and Saif (2015) investigated the youth adoption of m-government services in Egypt using a survey method for data collection, and the findings

revealed that perceived usefulness, compatibility, awareness, social influence, and face-to-face interactions contribute to the intention to use m-government.

Despite these contributions, m-government is still an evolving study area (Wirtz et al., 2021; Zhou et al., 2024) and requires more research in the areas of citizens intention to use m-government services (Wirtz et al., 2021) and factors affecting citizens use of m-government services (Huda, 2023; Zhou et al., 2024).

Theory

Framing Theory

Framing Theory explains how a communication source shapes public perception of a social or political issue (Nelson et al., 1997). It relates to the process through which individuals develop particular opinions of an issue (Chong & Druckman, 2007). Frames help people structure and interpret their experiences, shaping how they understand and react to events (Goffman, 1974). As a key concept in public opinion and media studies, framing theory plays a crucial role in shaping public discourse and attention. Chong (1993) states that a frame in communication can be outlined only in relation to a defined issue, event, or political figure (Chong & Druckman 2007). The theory was applied in wide range of fields including, sociology, economics, psychology, cognitive linguistics, and communication, political science, and media studies (Borah, 2011).

Framing has considerable implications as it highlights some elements of reality while omitting others, which could potentially lead people to interpret subjects differently (Borah, 2011). Researchers have concluded that framing shapes how individuals develop a particular conceptualization of an issue or reorient their thinking about an issue (Chong

& Druckman, 2007). Additionally, framing has been shown to influence the collective public's attitudes and behaviors (Pan et al., 2022).

Scheufele (1999) conceptualized framing into four processes, frame building, frame setting, individual-level frame effects, and the relationship between individual frames and media frames. In the context of this research, frame building refers to the process by which journalists incorporate frames suggested by politicians into their coverage of an issue. Frame setting is the process associated with the salience of issue attributes and how stressing certain values and facts can affect opinion. Individual-level effects of framing relate to the behavioral, attitudinal or cognitive impact of media framing have on individuals. Frame setting is outlined in the main themes and narratives within those announcements, while individual-level effects are captured in the user reviews, which express sentiment in response to media coverage.

Furthermore, recent research on framing and digitalization has explored emerging topics such as digital activism and the dynamics of hybridization of new and old media (López-Rabadán, 2021). In response to the calls for more innovative approaches to framing theory, scholars have sought to systematize operational definitions of frames and examine framing effects development to adapt the theory to recent digitalization developments (D'Angelo et al., 2019).

The impact of media framing on citizen opinions

The media can shape public opinion by framing issues in a particular way (De Vreese, 2005). Media framing involves selecting and emphasizing certain pieces of information through images, stereotypes, metaphors, and messages while downplaying or omitting others. (Matthes, 2009). Psychological research has shown that mass media,

governments, and authorities can effectively utilize media framing to establish a narrative and set an agenda to profoundly influence public opinion even without any direct attempt at persuasion or manipulation (Nelson et al., 1997). Furthermore, research has concluded that media framing can alter public attitudes, and behaviors (Pan et al., 2022).

Media Framing is generally divided into two categories: positive framing and negative framing (Pedersen, 2014). Positive media framing deals with information that is presented as of higher gain (Tversky & Kahneman, 1986; Nabi et al., 2020). In the context of government services, positive media framing utilized in government services does not only influence awareness and understanding but also fosters a sense of trust and confidence between the individual and their government, which as a result accommodates the policy process (Soroka, 2002). Conversely, negative media framing deals with information that is of higher loss (Tversky & Kahneman, 1986; Nabi et al., 2020). Policymakers might use negative media framing to direct the public to oppose a certain issue and support policy changes (Pan et al., 2022).

Framing scholars have combined media content analysis with survey data to identify connections between aggregate framing trends and aggregate shifts in public opinion (Oxley, 2020). For example, Nelson et al. (1997) examined how framing influences political attitudes in Americans, emphasizing psychological mechanisms beyond simple belief change. Similarly, Pan et al. (2022) explored how government-controlled media can be used to re-frame policy issue and change public opinion toward policies in China. Hu (2018) explored the relationship between the United States government and media in promoting policy philosophy and objectives. Additionally, Lecheler et al. (2015) conducted a survey experiment and exposed participants to pre-established frames to

study how emotions mediate framing effects on opinions about immigration. Neuman et al. (2014) utilize big data to explore attention and framing related to twenty-nine political issues in the United States during 2012. Further, Watimin et al (2023) applied sentiment and content analysis to study how framing theory can predict users' sentiment in predicting crises based on selected Facebook posts.

Citizens' perceptions include how particular, subjective experiences are formed and guide the behaviors by the information reaching the individual (Rogers, 2017) and includes how citizens organize and interpret their impressions towards the information they receive (Dhingra & Dhingra, 2011). Citizens have high expectations of services offered by the government, and they believe that these services will help in meeting their needs and improving their life (Sigwejo & Pather, 2016). Providing services that meet the needs and expectations of citizens will influence citizens' desire to use government electronic services and ultimately result in user satisfaction (Sigwejo & Pather, 2016; Porumbescu, 2016).

A citizen-centric approach is particularly significant for developing countries, where technological advancements and digital connectivity often lag behind those of developed nations (Sigwejo & Pather, 2016). Citizen perceptions drive citizen behavior, in order to reduce the distance between citizens and government, improved understanding of citizen perceptions is required, therefore, the government can set a course for changing the relationship with citizens by listening and acting on their perceptions (Glaser & Denhardt, 2000; Haug et al., 2024).

A main challenge for governments is to investigate and understand the needs and expectations of citizens (Sigwejo & Pather, 2016). Governments often consider

technological solutions rather than the users' needs in determining the design of government electronic services (Sigwejo & Pather, 2016). Including the voice of citizens in e-government decision-making requires a robust understanding of the determinants of users' satisfaction (Kowalski et al., 2020). Citizens build their perceptions of government and its performance through their personal experiences (Glaser & Denhardt, 2000). Emerging technologies, including social media analytics, are transforming the governance model with the new role of government and citizens (Gil-Garcia, 2012; Agostino & Arnaboldi, 2016). To effectively improve citizen-government relations, governments should honor citizen perceptions (Glaser & Denhardt, 2000). It is important for governments to consider the citizen-centric approach and focus on what the citizens really need. Instead, what services government agencies can provide (Sigwejo & Pather, 2016). The citizen-centric approach advocates for the provision of citizen-oriented services that meets the citizens' expectations (Sigwejo & Pather, 2016).

Government mandatory use of electronic services

Governments have increasingly begun to mandate the use of e-government services (Alkrajji, 2020). Through the implementation of policies and regulations, governments can enforce the adoption of m-government services, creating a mandatory environment for citizens (Ishengoma et al., 2019). In such cases, citizens have no choice but to comply with mandated digital services (Alkrajji, 2020). Research on the effects of mandatory e-government adoption remains limited. Chan et al. (2010) discussed the mandatory technology adoption for the specific context of an e-government technology, highlighting the importance of external factors—such as awareness, assistance, convenience, self-efficacy, trust, avoidance of personal interaction, flexibility, and compatibility—in

shaping three key UTAUT constructs (performance expectancy, facilitating conditions, and effort expectancy, which, as a result, influenced the citizens' satisfaction.

Research has shown that the mandating of information systems might cause a resistant response from the public (Bhattacharjee et al., 2018). However, resistant behavior varies widely, ranging from non-usage and non-compliance to more active forms of resistance, such as, workarounds or sabotage (Laumer et al., 2016). In cases where citizens feel they have little control over mandatory digital services, they often resort to emotion-focused coping strategies. These strategies may include selectively avoiding or withdrawing from the event, living in denial, or being frustrated or disappointed (Bhattacharjee et al., 2018).

Further, Alkraihi (2020) investigated citizen satisfaction with mandatory e-government services related to the academic admission system and concluded that the perceived usefulness of and trust mediated the indirect effect of system quality and information quality on satisfaction. Additionally, system quality exhibited the strongest overall effect on citizen satisfaction.

In the information system literature, scholars addressed the impact of mandatory use of technology on users and concluded that resistance to change is a key factor in the context of mandatory information system usage in organizations (Laumer et al., 2016, Klaus et al., 2010). Additionally, punishment expectancy positively affects information technology usage in a mandatory setting (Liang et al., 2013). Users may show different responses for mandated information systems such as including engagement, compliance, reluctance, or deviance, and those responses tend to emerge over time in the coping process (Bhattacharjee et al., 2018).

M- government in Jordan: Sanad Mobile Application

Sanad is the m-government application in Jordan. Sanad is an Arabic word that means “Support.” It is a common word used in Jordan for stating help and support in a particular situation. Sanad allows access to the digital services provided by the government of Jordan with a single e-ID as a gateway to all services. The mobile application is available on Google Play Store, Apple Store, and Huawei. The Ministry of Digital Economy and Entrepreneurship developed the app in partnership with other governmental agencies and private sector institutions. The app was recognized as one of the top five government apps worldwide in the World Summit Award 2022.

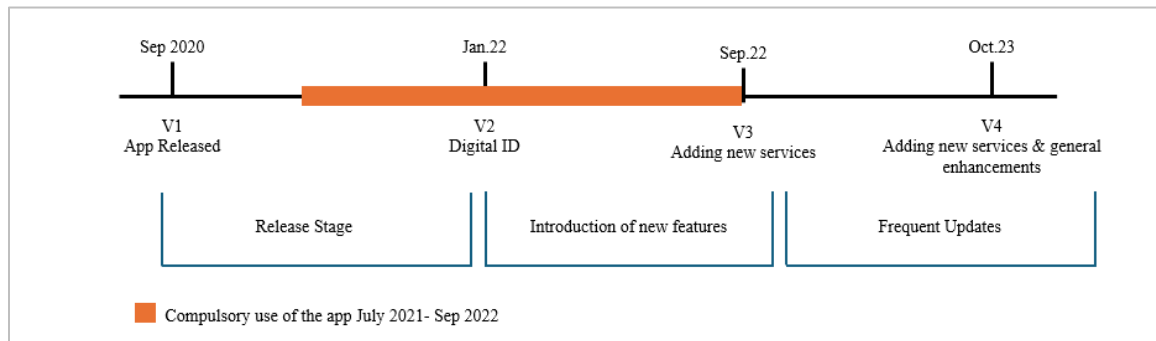
Sanad was first used in 2020 during COVID-19. It was linked with the Ministry of Health records, where the app gave individuals a green profile if they were fully vaccinated and gave a red profile to those who did not take the two doses of covid-19 vaccine and did not have a recent negative PCR test result, individuals with a red profile on Sanad were banned from entering any public facility in Jordan during the COVID response time. In 2022, the government announced major updates and added more services to the app, such as digital signature, court case inquiries, company inquiries, employment inquiries, and penalties inquiries for different government agencies. The update also included personal digital documents for citizens such as personal ID, birth certificates, social security, family book, driving license, vehicle license, school, and university certificates.

To enable citizens to use the services, the digital ID should be verified through Sanad stations available across Jordan. The App home screen includes six key features: personal information, digital documents, government services, digital signature, bill payments, and

health ID. Other features included are emergency numbers, the latest news, weather, feedback, suggestions, and complaints.

The development of Sanad Mobile Application went through three major phases since its inception in September 2020, till 2023, as figure 1 illustrates. The first one is the initial release phase which was associated with the mandatory use of the app for health ID verification, the second phase included the introduction of new features; the digital ID which was launched in January 2022, and the third phase included frequent updates since September 2022 where the government continued the expansion of e-services and provided general enhancements to the app. Each of those stages had an impact on the citizens' feedback and sentiment.

Figure 1: Application Development Timeline



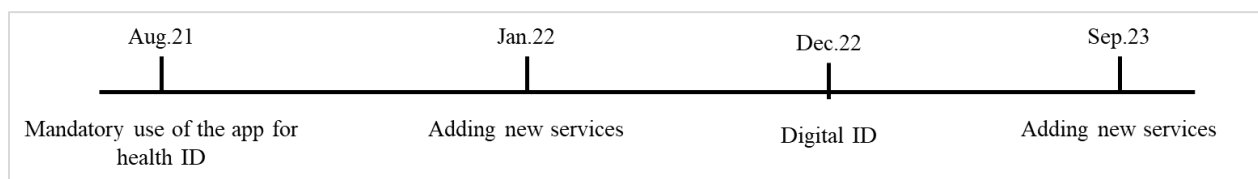
Initially, when the app was launched, it entered the initial release stage (Kaushik & Gokpinar, 2023). This stage includes the first version of Sanad app with the functions required for health ID verification. At the initial release stage, user feedback is collected, and developers identify areas for improvement for subsequent updates to enhance user experience, which is important for the app's success (Lee & Raghu, 2014). The initial versions in general lack the functionalities that users expect, which may lead to poor perceptions and sentiment (Comino et al., 2019).

Then, the introduction of new features is a key aspect of the application's evolution (Kaushik & Gokpinar, 2023). This stage can involve adding functionalities that enhance user engagement, improve usability, enhance app performance, or make it more appealing to users. This stage involved introducing the digital ID as a new feature in Sanad app.

The next stage is the frequent updates, which do not only include new features, but it also involves quality enhancements of existing functionalities and bug fixing to ultimately improve the user experience (Comino et al., 2019). Sanad mobile app has been through two major updates to include additional services in versions 3 and 4 and enhance the overall app performance for a better experience.

Figure number 1 shows the timeline and indicates the dates for the key news announcements related to the m-government application.

Figure 2: Media Narratives Timeline



Methodology and data

Methods

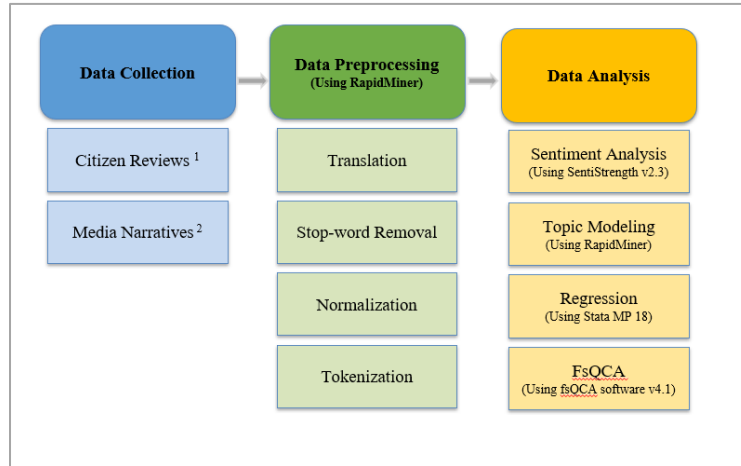
This research employed a multi-method approach to analyze citizen sentiment, thematic patterns, and the relationship between user sentiment and media framing. First, sentiment analysis was applied to assess the emotional tone of user reviews across four distinct application versions and to analyze sentiment in media coverage related to the m-government application. Sentiment analysis was chosen because it enables large-scale, automated identification of public sentiment, offering insights into how emotions

fluctuate in response to app updates and media narratives (Liu, 2022). Next, topic modeling was employed to identify and categorize the main themes within both user reviews and media articles. This method allows for an unsupervised exploration of dominant discussion topics, revealing recurring concerns, praise, and criticisms of the application over time (Blei et al., 2003). Topic modeling complements sentiment analysis by providing context to sentiment shifts, helping to explain why certain emotions are expressed in user reviews. Both sentiment analysis and topic modeling contribute to greater objectivity in textual analysis by reducing researcher bias and systematically identifying patterns in large-scale text data (Stone et al., 1966). Following this, regression analysis was applied to examine the relationship between user sentiment and media framing. Regression analysis was selected to quantify the extent to which sentiment trends in user reviews align with variations in media coverage, allowing for the identification of significant predictive relationships between framing effects and public response (Wooldridge, 2016). Finally, fuzzy-set Qualitative Comparative Analysis (fsQCA) was used to generate truth tables for both positive and negative sentiments in user reviews. FsQCA was chosen because it allows for the identification of complex causal relationships and configurations of conditions that lead to specific sentiment patterns, providing a more nuanced understanding of public opinion formation in the context of m-government adoption (Ragin, 2009).

Each of the methodologies are explained in more detail in Appendix 3.

The analysis workflow included four phases; data collection, data-preprocessing and analysis (Ibrahim & Wang, 2019; Li et al, 2023), as depicted in figure 2 below:

Figure 3: Analysis workflow



Data and variables

This study utilized two datasets. The first dataset comprised 10,725 user reviews of the m-government application, extracted from the Google Play Store, along with their respective dates and app versions. The reviews spanned from September 2020 to December 2023. The second dataset included media announcements related to the Sanad application, containing the news agency source, date, title, and full content.

To prepare the data for sentiment analysis and topic modeling, several preprocessing steps were applied. First, Arabic text was translated into English to maintain consistency across the dataset. Non-Arabic and non-English reviews were removed. Next, standard text-cleaning techniques were implemented, including stop-word removal, case normalization, tokenization, and stemming to refine the text and enhance model

¹ Extracted on January 2024, using google play scraper API

² Extracted on April 2024, from Google news, using keywords “Sanad” or “Sanad App” or “Sanad Application” in both languages Arabic and English, it includes the news published between 2020 and 2023 in Jordan by online newspapers. The search did not include social media platforms.

performance (Ibrahim & Wang, 2019; Li et al, 2023). Table 1 indicates the description of variables for each dataset.

Table 1: Description of Variables

Dataset	Variable	Description	Type
User Reviews	Content	The review posted by the user	String
	Date	The review date	Date
	Sentiment Score	Sentiment score ranging between -5 to 5	Continuous
	Compulsory	Indicates whether the review was during the app compulsory period,	Binary
	Stage 1	The initial release phase	Categorical
	Stage 2	New features introduction phase, which involved introducing the digital id feature	Binary
	Stage 3	Frequent updates phase, which included adding more services to the app.	Binary
Media announcements	Content	The press release content	String
	Date	The date of the press release	Date
	Topic 1	If the press release is related to the compulsory use of the app.	Binary
	Topic 2	If the press release is related to adding new services to the app.	Binary
	Topic 3	If the press release is related to the digital ID	Binary
	Sentiment 1	The sentiment score for topic 1	Continuous
	Sentiment 2	The sentiment score for topic 2	Continuous
	Sentiment 3	The sentiment score for topic 3	Continuous
	Stock 1	The discounted score for topic 1 sentiment	Continuous
	Stock 2	The discounted score for topic 2 sentiment	Continuous

	Stock 3	The discounted score for topic 3 sentiment	Continuous
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Results

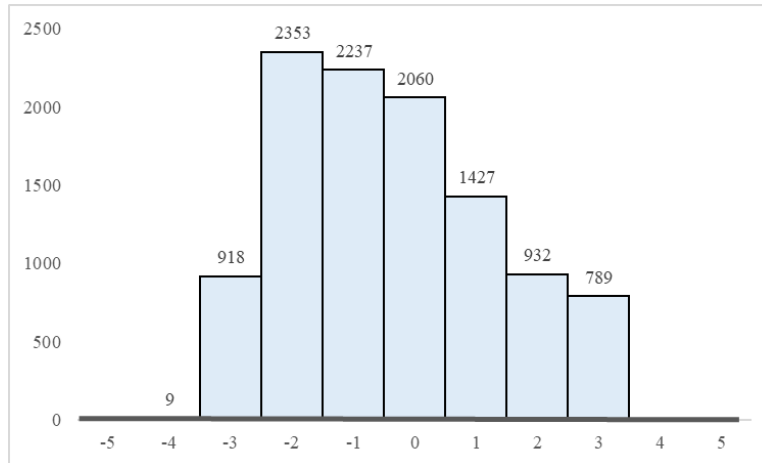
Descriptive Statistics

The majority of the sentiments expressed in the citizens' reviews were negative, which accounted for 55% of all sentiments, followed by the positive, which accounted for 26%, and the neutral sentiment, which accounted for 19%. Table 2 shows the distribution of sentiments during the years 2020-2023, throughout analyzing the number of reviews over this time span, the reviews were the highest in the year 2021, which accounted for 67% from all the reviews and the majority of the sentiments in that year were negative, which accounted for 74% from the sentiments, while the majority of the reviews in the years 2022 and 2023 were positive and accounted for 56% and 76% from the reviews, respectively. The frequency of the negative sentiments was mainly in the categories of -1 and -2, and the frequency of positive sentiments was between 1 and 3, as Figure 3 depicts.

Table 2: Distribution of Sentiments

Sentiment	2020	2021	2022	2023	Total
Negative	96	4,952	356	113	5,517
Neutral	37	1,348	197	478	2,060
Positive	13	407	703	2,025	3,148
Total	146	6,707	1,256	2,616	10,725

Figure 4: Distribution of Sentiment Scores



Sentiment Analysis

To analyze the trend of citizens sentiment across the evolution of the application sentiment analysis techniques were applied, the sentiment scores were at their lowest level in the initial release phase, and it slightly improved in with the introduction of new features, then it had slight drop before it goes app again in the frequent updates phase, as per figure number 4 depicts.

As per figure 5 shows, the positive sentiment throughout different phases was between 1 to 1.5 and increased slightly above 2 in the second half of 2023. On the other hand, the negative sentiment scores reached -3 in during the initial release phase and improved to -1 in with the introduction of new features, then it dropped again with the frequent updates as shown in figure number 6.

Figure 5: Sentiment Scores

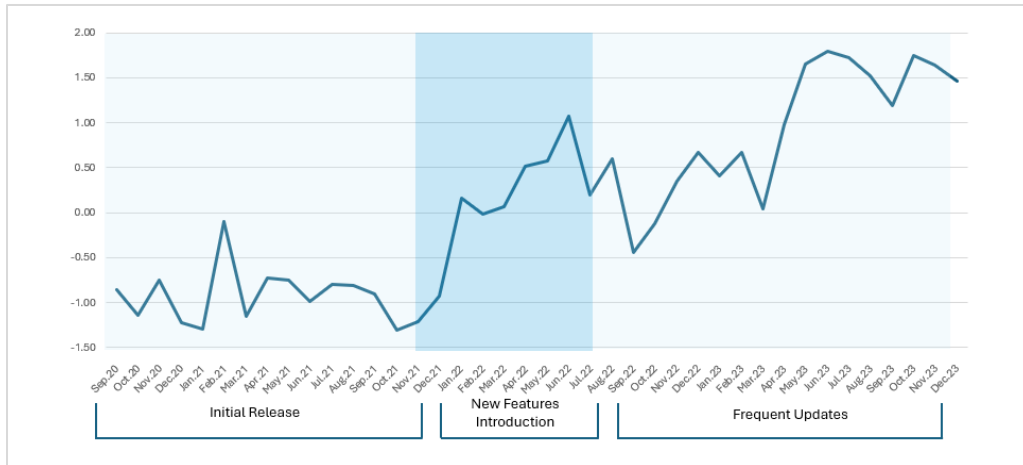


Figure 6: Positive Sentiment trend

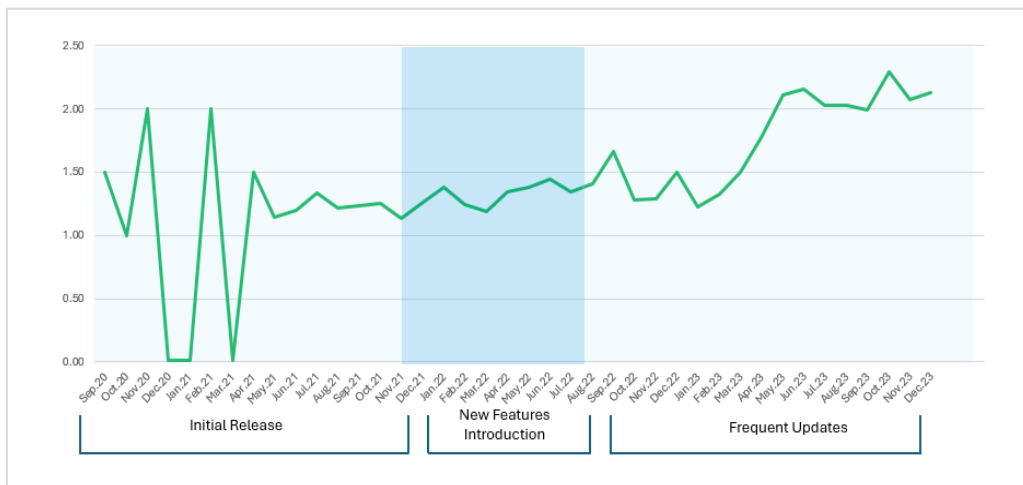
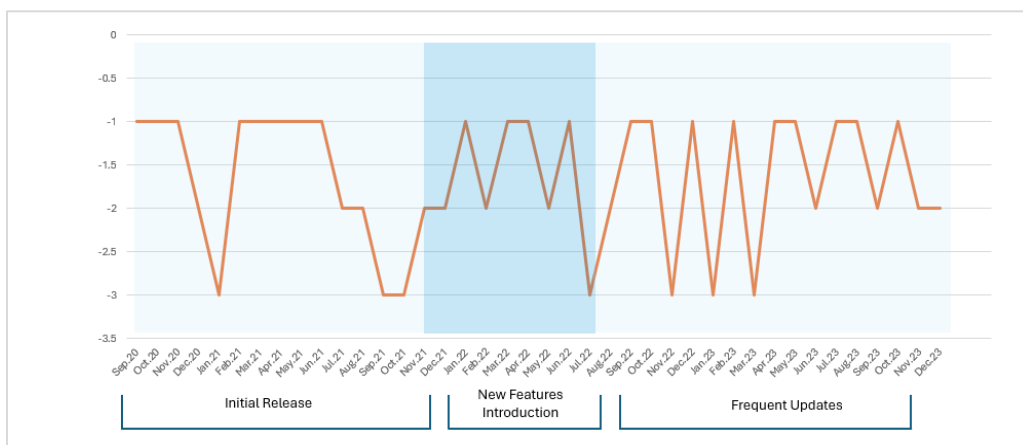


Figure 7: Negative Sentiment trend



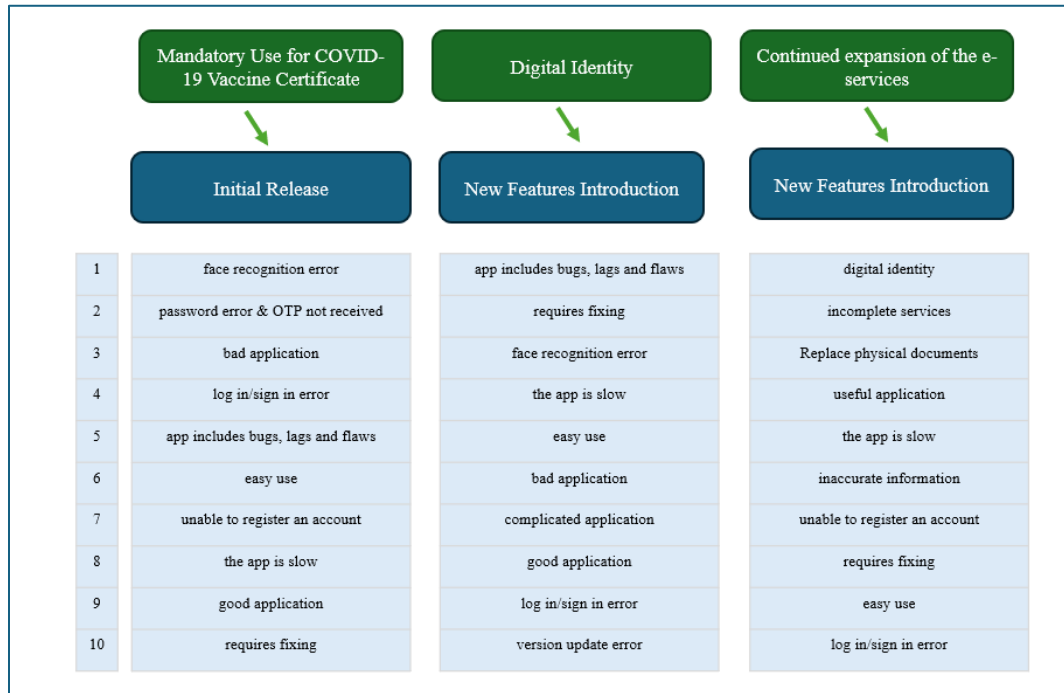
Topic Modeling

To answer the research questions related to what the most common topics of are concerns the users expressed while using the Sanad application, we applied topic modeling. The user expressed certain concerns throughout the application development stages as figure 7 depicts, where the initial release phase topic modeling results revealed major concerns related to the application features, which lie under the developer's responsibility, such as face recognition error and failure to recognize the individual by matching their selfie with the photo on their national identity card, this error continued to be a concern for the introduction of new features stage as well. In addition to the password error and not receiving the one-time password (OTP) code on the users' mobile number to enable them to reset the password and access the application, moreover, the sign-in error continued to be a concern during the three stages, where citizens may not be able to access their accounts after entering their login credentials. Moreover, the users expressed a concern related to the speed of the application through the app development. Citizens also mentioned in their reviews that the application includes a lot of bugs and requires fixing. On the other side, citizens expressed a positive attitude in describing the application as good application and easy to use.

Additionally, concerns were expressed related to the government initiatives and strategies in the frequent updates phase, where the citizens mentioned that the services offered through the application are incomplete, the citizens information is inaccurate such as date of birth or passport number, and there is a lack of support and help desk, moreover, the government entities still do not accept the digital identity and the digital document as replacement of the physical documents. From the LDA output, we observed several

exciting concepts that have an impact on the user experience such as face recognition error, inability to sign in and keeps disconnecting.

Figure 8: Topic modeling results for the users' reviews



Regression Analysis

Linear regression analysis was employed to uncover the relationship between citizens' sentiment as the dependent variable and the policymakers' actions including as media framing, mandating the use of the app, and app development and explanatory variables.

Table 3: Linear Regression

	(1)	(2)	(3)	(4)
Compulsory	-2.038*** (0.029)	-0.269*** (0.053)	-2.020*** (0.030)	-1.762*** (0.032)
Stage1		0.000 (.)		
Stage2		1.536*** (0.053)		
Stage3		0.891*** (0.076)		

Topic 1			-0.017 (0.072)	
Topic 2			0.844*** (0.175)	
Topic 3			0.549*** (0.141)	
Stock 1				-0.363*** (0.026)
Stock 2				0.449*** (0.024)
Stock 3				0.325*** (0.031)
_cons	6.022*** (0.024)	4.113*** (0.051)	6.000*** (0.025)	5.838*** (0.026)
<i>N</i>	10725	9062	10725	10725
Log likelihood	-18871.865	-14786.681	-18852.745	-18514.295

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3 shows the linear regression results. The first model indicates the impact of the mandatory use of the app on the citizens sentiment as dependent variable, which had a negative and significant impact $\beta = -2.038$ ($p < 0.01$), the marginal effect suggests that the sentiment score decreases by 0.16 for the mandatory usage, which corresponds to a 22% decrease at the sample mean. The second model shows the impact of the application development stages on the citizen sentiment, where both the second and third stages had significant and positive impact with $\beta = 1.536$ ($p < 0.01$) and $\beta = 0.891$ ($p < 0.01$) respectively, the marginal effect suggests that the sentiment score increases by 1.2 for the improvements associated with stage 2 (introduction of new features, the digital ID), which corresponds to a 306% increase at the sample mean, and increases by 1.1 for the improvements associated with stage 3 (frequent updates), which corresponds to 403%. The third model shows the impact of the press releases on citizens sentiment, where both topic two, related to new services, and three related, to the digital ID, had significant and positive impacts $\beta = 0.844$ ($p < 0.01$) and $\beta = 0.549$ ($p < 0.01$) respectively. The marginal effect suggests that the sentiment score decrease by -0.22 for the second topic, which

corresponds to a 366% decrease at the sample mean., and the marginal effect suggests that the sentiment score increases by 1.4 for the third topic, which corresponds to a 104% increase at the sample mean. The fourth model shows the impact of the sentiment of the news announcements on the citizens sentiment, which is negative and significant for the first topic related to the mandatory use of the app $\beta = -0.363$ ($p < 0.01$), and positive and significant for the second and third topic $\beta = 0.449$ ($p < 0.01$) and $\beta = 0.325$ ($p < 0.01$), respectively. The marginal effect suggests that the sentiment score decreased by 0.31 for the first topic sentiment, which corresponds to a 106% decrease at the sample mean, and increased by 0.26 for the second topic sentiment, which corresponds to a 107% increase at the sample mean, and finally increased by 0.03 for the third topic sentiment, which corresponds to a 31 % increase at the sample mean.

FsQCA

To identify the most important factors affecting citizens' sentiment on the m-government application, this study used a fuzzy-set Qualitative Comparative Analysis (fsQCA). We generated the truth tables for the positive and negative sentiment variables, as shown in the table below.

Table 4: Configurations for positive and negative sentiment

	Positive sentiment				Negative sentiment				
	HP1	HP2	HP3	HP4	HN1	HN2	HN3	HN4	HN5
Compulsory	⊗	○	⊗	⊗	○	●	○	●	⊗
Stage 1	⊗	⊗	⊗	⊗	●	●	●	●	●
Stage 2	○	●	●	●	○	○	●	⊗	●
Stage 3	●	●	●	●	⊗	⊗	○	⊗	●
t1	⊗	⊗	○	⊗	⊗	⊗	⊗	○	⊗
t2	⊗	⊗	⊗	○	⊗	○	⊗	⊗	⊗
t3	⊗	⊗	⊗	⊗	⊗	⊗	⊗	⊗	○
Consistency	0.805	0.837	0.844	0.840	1.000	1.000	1.000	1.000	1.000
Raw Coverage	0.414	0.276	0.267	0.264	0.924	0.841	0.053	0.857	0.022
Unique Coverage	0.157	0.002	0.011	0.007	0.086	0.003	0.001	0.049	0.001

Overall Consistency	0.997
Overall Coverage	1.000

HP: High priority configurations for positive sentiment.

HN: High priority configurations for negative sentiment.

The black circles (●) indicate the presence of the condition, and crossed-out circle (⊗) denotes the absence of one, and the blank circle indicates the do not care status of the condition (○).

The results highlighted that positive sentiment results from specific combinations of the presence and non-presence of various conditions associated with the application. The configurations HP1 to HP4 led to positive sentiment, configuration HP1: Positive sentiment is generated when conditions using the more advanced version of the application associated with more enhanced features and additional services, voluntary use of the app, and without related press releases. This suggests that a favorable user experience is associated with more enhanced app features and voluntary use.

Configuration HP2: Provides another pathway to positive sentiment, highlighting that positive sentiment requires the enhanced application feature and the voluntary use of the app is indifferent. Configuration HP and HP4: Here, positive sentiment arises through the app's various stages, specifically moving from stage 2 of enhanced features to frequent updates.

The variety of these configurations shows multiple pathways to achieve positive sentiment. It indicates that while certain factors such as the presence of the enhanced version and non-presence of compulsory use are consistently present in configurations leading to positive sentiment, it also shows that press releases topics did not have an impact on the positive sentiment.

The fsQCA analysis also reveals specific pathways (HN1 to HN5) that lead to negative sentiment. Configuration HN1: this option shows that negative sentiment occurs when the app is in the initial release phase, which is associated with basic features. Configurations

HN2 and H24 show that negative sentiment results from compulsory use of the application and use of the initial release version, while HN3 and HN5 did not associate the negative sentiment with compulsory use as the other configurations, the negative sentiment also resulted from the use of the initial release version.

These configurations demonstrate that negative sentiment is often associated with the initial release phase; while two options did not care about the compulsory use of the app, two options showed the negative sentiment is associated with compulsory use. Similar to the positive sentiment results, the presence of news topic does not impact citizen sentiment.

Discussion

This research provides critical insights into how policymakers' actions—such as media framing, mandating app usage, and app development— shape citizen sentiment toward m-government applications. The findings extend prior research on e-government and m-government adoption by revealing how sentiment evolves over time in response to both technological improvements and policy interventions (Shareef et al., 2016; Wirtz et al., 2021).

The trend analysis of the citizen sentiment across the different phases of the application revealed the dynamic relationship between technological improvements and user satisfaction. The initial release phase recorded the lowest sentiment scores, reflecting widespread user frustration due to functionality gaps, technical errors, and usability issues. This aligns with studies indicating that early-stage mobile applications often face adoption barriers due to usability shortcomings and lack of key functionalities (Comino et al., 2019; Shareef et al., 2016).

As the application evolved with new features and frequent updates, citizen sentiment gradually improved, confirming the strong correlation between application enhancements and user satisfaction (Zahidi et al., 2021; Verma, 2022). However, this improvement was not uniform across all aspects of the application, supporting prior literature that suggests user expectations evolve with technological advancements, requiring iterative improvements (Fleischmann et al., 2016). This study contributes to the literature on m-government usability by demonstrating that feature expansion alone is insufficient for sustained positive sentiment; usability and communication strategies must also be prioritized (Franzmann et al., 2019).

The topic modeling analysis revealed important concerns at each development stage of the m-government application, reinforcing previous findings that user feedback is a crucial but underutilized resource in public sector innovation (Hu et al., 2019; Farzadnia et al., 2024). During the initial phase, negative sentiment was primarily associated with technical issues such as face recognition errors, registration difficulties, and password malfunctions. This supports research indicating that first-generation digital services often fail to meet user expectations due to insufficient testing and lack of citizen input during development (Comino et al., 2019; Alkrajji, 2020). As the application progressed, new concerns emerged alongside improvements. The introduction of updates led to topics related to updating errors, inaccurate information, incomplete services, and uncertainty regarding digital identification and the replacement of physical documents. This reflects the ongoing challenge of balancing feature expansion with usability and trust-building efforts, a recurring issue in e-government service design (Fleischmann et al., 2016). The presence of persistent concerns—such as slow app speed and login issues—across all

development stages suggests that certain structural issues require sustained attention from policymakers and developers. This finding strengthens prior arguments that m-government adoption is not only about adding new functionalities but also about ensuring consistency, stability, and reliability (Shareef et al., 2016).

A key contribution of this study is its analysis of the impact of mandatory adoption on user sentiment, which builds upon prior research that has examined resistance to imposed digital services in general but has rarely explored it in the m-government context (Laumer et al., 2016; Bhattacharjee et al., 2018; Alkraihi, 2020). The regression analysis confirmed that mandatory use negatively influenced citizen sentiment, reinforcing the argument that coercion leads to dissatisfaction, lack of trust, and resistance (Liang et al., 2013; Wirtz et al., 2021). This study expands the literature by showing that while mandating m-government services may drive initial adoption rates, it does not necessarily translate into positive user experiences or long-term engagement.

Additionally, media framing was found to strongly influence citizen sentiment, demonstrating that news coverage can significantly shape public trust and perceptions of digital government services. This aligns with research in media and technology adoption, where framing effects have been shown to influence public attitudes toward emerging technologies and digital governance initiatives (Boulianne, 2020; Gilardi et al., 2022). Positive framing can enhance public confidence and drive adoption, while negative framing—particularly narratives emphasizing security flaws, inefficiencies, or enforcement policies—can amplify distrust and resistance. This study extends media framing research into the technology-oriented public sector domain, offering new evidence of its impact on m-government sentiment formation.

Beyond traditional regression analysis, fsQCA provided deeper insights into the conditions that shape public sentiment toward m-government applications. This method revealed interactions between multiple factors, such as usability, mandatory policies, and media representation, which collectively influence citizen perceptions. The findings support prior research that m-government adoption is influenced by a complex interplay of technological, behavioral, and policy-driven factors (Ragin, 2009; Huda, 2023).

Conclusion

This study uncovered the citizens' concerns and emerging topics implied in their reviews of the m-government application, using topic modeling, regression and sentiment analysis. The findings highlight how the citizens' sentiment evolves in response to policymakers' actions, including media announcements, mandatory app usage, and application development. This study provides valuable insights into the factors shaping public perceptions of m-government services and contributes to a more nuanced understanding of user engagement with digital public services.

This study makes several contributions to the existing literature on m-government adoption, digital public services, and media framing. It extends research on user satisfaction in m-government by analyzing sentiment evolution over time, rather than treating adoption as a static outcome. It expands the literature on mandatory technology adoption by demonstrating its specific impact in an m-government context, reinforcing prior studies on user resistance to impose digital services. Additionally, it bridges media framing theory with digital government research by showing how news narratives significantly influence citizen engagement with m-government services. From a methodological perspective, it introduces an innovative approach in m-government

research, combining four analytical methods and providing a richer understanding of the interactions between policy decisions, usability, and media perception. Furthermore, it demonstrates that feature expansion alone is insufficient for sustained positive sentiment, reinforcing the importance of usability improvements and communication strategies in m-government adoption.

Beyond theoretical contributions, the findings offer important policy implications for improving m-government adoption and user satisfaction. Governments should focus on continuously improving the application functionalities and expanding the scope of services offered to enhance user experience. Establishing a dedicated help desk with AI-powered chatbots and automated support systems can provide ongoing technical assistance, particularly for frequent login issues, service navigation challenges, and identity verification concerns. Awareness campaigns and training programs for government entities on how to verify the citizen identity digitally and how the digital ID can be used as a replacement of the physical documents are essential. Additionally, governments should periodically analyze the sentiment in the m-government application reviews to uncover insights hidden in the citizens' comments development, especially when analyzed with the topic modeling that can help identifying the root cause behind low adoption rates and citizens' dissatisfaction, and help the government to improve the app and explore further areas for continued development.

While this study provides valuable insights, it has several limitations. The findings may have limited generalizability due to the specific geographical focus and timeframe of the data, as sentiments may vary across different regions, countries, and time periods.

Additionally, the dataset was limited to user reviews and did not include demographic

attributes such as age, location, and education level, which could have influenced the expressed topics and sentiments. Future research can expand this approach by applying the same sentiment analysis and topic modeling techniques in different governance systems to assess cross-national variations in m-government sentiment. Incorporating demographic data could provide further insights into how factors such as age, education level, and digital literacy shape citizen perceptions of m-government services. Furthermore, examining longitudinal changes in sentiment beyond the initial years of adoption could reveal how user satisfaction and expectations evolve over time.

Chapter 4

Bridging the Gap in Smart Government: From AI Readiness to AI Implementation

Abstract

This research investigates the impact of technology, organization, environment, and governance dimensions on the gap between artificial intelligence (AI) readiness and implementation across countries. We extend the widely used Technology–Organization–Environment (TOE) framework by incorporating governance as an additional dimension, creating the TOE-G framework to interpret the results. The analysis, based on cross-national data from 77 countries, reveals that technology and environmental factors significantly increase the likelihood of AI implementation, while the governance exerts a negative and significant effect. This counterintuitive finding suggests that heavy investment in governance frameworks may delay rather than accelerate AI implementation. The research contributes to the AI adoption and smart government literature by offering a more comprehensive model of national-level technology implementation. It also provides practical implementations for policymakers on balancing governance with technological and environmental enablers to move from being AI-ready to achieving tangible AI implementation in public services.

Keywords: Artificial intelligence, Smart Government, Public Services, Transformation Innovation, AI Readiness, AI Implementation, TOE framework, AI Governance, Technology Adoption

Introduction

Recently, the world is witnessing a promising transformation in the public sector, as governments are investing heavily in emerging technologies (Guenduez et al., 2018). Among these, artificial intelligence (AI) has become a strategic priority worldwide, with governments seeking to improve service delivery and streamline their internal operations (Hjaltalin et al., 2024). Smart government is considered the highest modernization phase of public services (Hujran et al., 2023). It represents the evolution of e-government, into a more effective, efficient, and transparent model that leverages cutting-edge technologies such as AI, Internet of Things (IoT) and blockchain (Anthopoulos et al., 2021).

AI is a key enabler for smart government. For instance, chatbots (Androutsopoulou et al., 2019; Desouza et al., 2020), AI-based self-service tools (Chen et al., 2021), AI voice robots (Wang et al., 2021), predictive analytics for fraud detection (Desouza et al., 2020; Chatterjee et al., 2022), and AI-powered surveillance systems (Yigitcanlar et al., 2023) illustrate how AI can enhance communication with citizens, improved citizens' experience, reduce administrative burdens, and generate cost efficiencies (Androutsopoulou et al., 2019; Chen et al., 2021, Hujran et al., 2023). Moreover, smart government enables real-time, data-driven decision-making, promote citizen engagement, and balance innovation with privacy, equity and trust concerns (Terán et al., 2024).

Despite increasing investments in AI research, AI in public services remains a relatively young field of inquiry (Wirtz et al., 2019; Sun & Medaglia, 2019; Yigitcanlar et al., 2023; Neumann et al., 2024). Existing studies highlight three important gaps. First, most research emphasizes AI readiness, while empirical evidence and research on actual AI

implementation in the public sector remains scarce (Mergel et al., 2024; Hjaltalin et al., 2024; Neumann et al., 2024). Second, scholars have emphasized the need for more cross-country comparative studies and empirical analyses rather than predominantly conceptual work (Wirtz et al., 2019; Chandra & Feng, 2025). Third, successful smart government requires not only technological progress but also advances in government management and policy, which is an area where governance gaps remain underexplored (Gil-Garcia et al., 2016; Wirtz et al., 2022). All in all, while the literature highlights the importance of implementation and governance, systematic empirical evidence explaining why countries struggle to move from readiness to implementation is missing.

This gap in literature mirrors a striking gap in practice. According to the Global AI index, the average implementation score of AI is only 13%, having United States and China at the top of index with score of 100%, and 54%, respectively, and the remaining countries in the index with scores below 50%. By contrast, the average AI readiness capabilities for those countries is 72% with the majority scoring above 50% (Tortoise Media, 2024). This discrepancy reveals a substantial disparity between governments' readiness for AI and their ability to translate readiness into actual implementation (see Figure 1). Addressing this gap is critical for policymakers seeking to design targeted strategies for smart governance. Therefore, this research aims to answer the following question:

RQ: Why do countries lag behind in actual AI implementation despite relatively high levels of AI readiness?

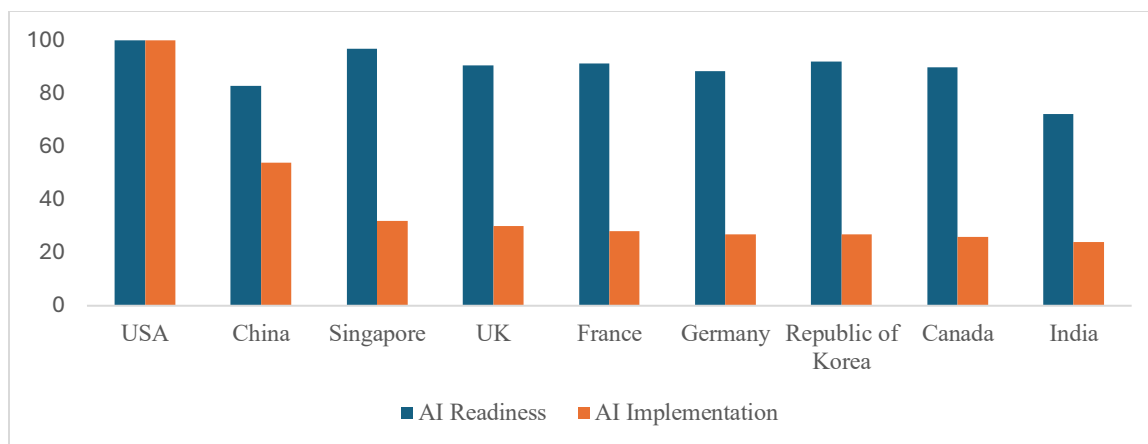


Figure 1: Top 10 countries in AI implementation

To answer this research question, we employ the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), widely used to study innovation adoption (Alsheibani et al. 2018; Al Hadwer, 2021; Wu & Chen, 2014; Lin, 2014; Malik et al., 2021). While the TOE framework captures internal and external factors (Nguyen et al., 2022), its application at the country level requires attention to governance, an important factor for digital transformation initiatives at this level (Ndou, 2004; Meyerhoff Nielsen, 2020). Following calls to extend the TOE to enhance its explanatory power (Baker, 2011), we introduce the governance as an additional dimension, creating the TOE-G framework. In this context, the organizational dimension in the TOE covers the human capital side in terms of leadership, AI skills, the effectiveness of the government services, and to which it allows e-participation. The environment dimension relates to macroeconomic country-wide variables, while the governance related to AI strategies, laws and regulations designed to enhance the oversight of the AI applications in the public sector.

To explore our research question, we employ data from the AI Readiness Index and the Global AI Index on 77 countries to examine how technology, organization, environment,

and governance factors influence the translation of readiness into implementation. Results show that technology and environmental factors facilitate AI implementation, whereas governance — counterintuitively — exerts a negative effect, suggesting that overregulation and fragmented governance frameworks may delay adoption. The organizational dimension is largely insignificant, except when interacting with governance.

This study contributes to theory and practice in three ways. First, it advances theory by extending the well-established TOE framework with governance as a critical national-level dimension, thereby offering the TOE-G framework. While TOE has been applied extensively at the firm and organizational level, its explanatory power at the country level has been limited. The integration of governance into the TOE-G framework enables the model to account for institutional, regulatory, and policy factors that influence AI adoption in the public sector, strengthening its theoretical relevance for national and cross-country analyses. Second, it provides novel cross-country empirical evidence on why AI readiness does not automatically translate into implementation. This evidence directly addresses long-standing calls for comparative and empirical studies on AI adoption in the public sector and highlights the importance of considering macro-level conditions alongside organizational ones. Third, it offers practical guidance for policymakers seeking to close the readiness–implementation gap. The findings suggest that policymakers should resist the temptation to over-invest in governance frameworks at the expense of actual deployment and instead aim for a balance between regulatory safeguards and enabling conditions such as digital skills, infrastructure, and innovation ecosystems. This provides a roadmap for governments to design more effective AI

policies that move beyond readiness assessments and accelerate tangible progress toward smart government transformation.

Theoretical Framework

Smart government

Smart government refers to the government activities that creatively integrate emerging technologies with innovative strategies to deliver agile and resilient public services.

Becoming “smart” requires a forward-thinking approach that combines information, technology and innovation with institutional reorganization and modernization (Bojović et al., 2023; Gil-Garcia et al., 2014). The ultimate goal of smart governments is to create a sustainable, citizen-focused governance model that can adapt to the citizens changing needs in real-time (Terán et al., 2024).

The smart government is characterized with features such as integration, innovation, evidence-based decision making, citizen-centricity, sustainability, openness, resilience, and technology savviness (Algebri et al., 2017). These attributes signal a departure from earlier digital government paradigms. Whereas e-government and m-government primarily focus on digitizing services through the internet and wireless technology, smart government rethinks the role of government itself, transforming the relationship between citizen and government (Schedler et al., 2019).

Smart government is getting increasing attention from researchers and practitioners, being framed as the next revolution of e-government (Algebri et al., 2017; Anthopoulos et al., 2022; Hujran et al., 2023; Bojović et al., 2023). The adoption of smart technologies

such as blockchain, IoT and AI is expected to grow substantially, rendering public administration more intelligent and adaptative (Criado & Gil-Garcia, 2019; Bojović et al., 2023). These technologies not only digitalize existing processes but also enable computational approaches, such as big data analytics, policy modeling, and AI, that can reshape governance and service delivery (Althunibat et al., 2021; Criado & Gil-Garcia, 2019).

The potential benefits of smart government are well documented. It can reduce costs and improve efficiency by streamlining processes, lessen reliance on paperwork, and minimize human errors. It also enhances transparency and through open data platforms, increases citizen engagement via through digital participation tools (e.g. online forums, mobile applications, and social media), and improves service quality through AI powered applications (Terán et al., 2024). These outcomes can strengthen citizens' trust in government performance by creating more responsive and ubiquitous interactions (Hartanti et al., 2021).

At the same time, smart government initiatives face significant challenges. These include privacy and data security concerns, the risk of deepening digital divides, ethical and legal dilemmas, and the complexities of organizational change management (Terán et al., 2024).

Artificial Intelligence as an Enabler of Smart Government

AI refers to the capability of a computer machine to mimic the intelligence of a human and improving its own performance (Al-Mushayt, 2019). Although AI has existed for decades in specialized domains, recent advances in computing power, algorithms and

data availability have accelerated its integration into everyday public services. AI is increasingly positioned as a driver of future economies and governance models (Battina, 2017; Al-Mushayt, 2019) and it is gaining importance as governments seek to deliver smarter, leaner and more personalized services (Madan & Ashok, 2023). Consequently, public administrations' services supported by AI have emerged as a key topic among policymakers' agendas, leading to investments to explore AI possibilities of enhancing current service delivery models (Mergel et al., 2024).

The literature documented several use cases for the AI in the public sector. Examples include the Dutch childcare allowance, which employed AI for fraud detection; Michigan's automated unemployment insurance system, which reduces operating costs and flags fraud in unemployment insurance claims; and AI-supported healthcare services in China (Giest & Klievink, 2024; Sun & Medaglia, 2019). Across the European Union, an analysis of 250 cases revealed that AI is used mainly to support in improving public service delivery and internal management, with fewer applications in policy decision-making (Van Noordt et al., 2022). These examples suggest that AI can improve the speed, magnitude, and accuracy of information processing, ease access to public services, reduce paperwork, and free human labor for more complex tasks (Wirtz & Müller, 2019).

Governments are drawn to these benefits, expecting AI to cut administrative costs, improve citizen interactions (including virtual engagement), and strengthen innovation ecosystems by leveraging private sector advances (Battina, 2017; Wirtz & Müller, 2019). As traditional digital government services reach their limits, AI also holds promises for closing service delivery gaps and re-engaging citizens (Battina, 2017).

At the same time, Wirtz et. al (2019) highlights a wide range of challenges associated with AI adoption in the public sector, including technology (e.g., data quality, system integration), resources (financial feasibility, expertise), law and regulation (e.g., accountability, privacy, liability), ethics (fairness, discrimination, moral dilemmas), and societal impacts (e.g., workforce substitution, trust in AI, human-to-machine and machine-to-machine interactions). These challenges emphasize that AI adoption is not simply a technical question but also a deeply institutional, ethical and social one.

Reflecting these constraints, the Global AI Index reports that while average AI readiness across countries is 72%, actual implementation averages only 13%. Even leading nations diverge sharply, with the United States at 100%, China at 54%, and most other countries below 50% (Tortoise Media, 2024; Oxford Insights, 2024). This suggests that many governments possess readiness capabilities and strategies but struggle to translate them into tangible AI deployment.

Scholars have attributed this gap to several factors: poor awareness of AI potential, inadequate foundational technologies, low availability or quality of data, and poor digital skills (World Bank, 2020), legal and regulatory hurdles, limited financial resources, employees' resistance, and lack of leadership support or clear deployment guidelines (Mohamad et al., 2022). AI readiness studies further show variation across regions. For instance, African countries perform relatively well in data and infrastructure but lack strategies and supportive policy frameworks (Shonhe et al., 2024). Other studies find that leading countries in AI readiness often neglect transparency, privacy, and accountability (Nzobonimpa & Savard, 2023), and that readiness is shaped by factors such as

governance, infrastructure, human capital, innovation, socio-cultural context, and economic strength (Murko et al., 2024).

Emerging work also suggests that the benefits of AI may be overstated if issues of equity, ethics, justice, and fairness are ignored (Nzobonimpa & Savard, 2023). Further obstacles to readiness and implementation include economic indicators (GDP, unemployment), costs of AI talent, education systems (Montoya & Rivas, 2019), and government expenditure priorities (Socol & Iuga, 2024). Infrastructure, in particular, has been emphasized as a key precondition for successful adoption (Kulal et al., 2024).

Finally, the risks of AI adoption in government are significant. These include privacy violations through surveillance (Wirtz & Müller, 2019), ethical dilemmas in algorithmic decision-making (Henman, 2020; Motadi, 2024), and political or legal challenges of accountability (Sun & Medaglia, 2019). Overcoming these challenges requires not only substantial investment in infrastructure, skills, and leadership (Kulal et al., 2024; Tveita & Hustad, 2025), but also the development of ethical standards, regulatory frameworks, and responsible AI practices (Nzobonimpa & Savard, 2023; Wirtz & Müller, 2019).

The Technology Organizations-Environment (TOE) framework

To better understand why countries' struggle to translate AI readiness into implementation, this study turns to the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990). The TOE model framework has a strong theoretical basis, consistent empirical support and is among the most prominent and widely utilized theories of organizational technology adoption (Baker, 2011; Oliveira & Martins, 2011; Prakash, 2025; Alsheibani et al., 2018; Sun et al., 2024).

At its core, TOE identifies three dimensions that influence organizations' adoption decisions: technology, organization, and environment. The technology dimension consists of all of the technologies that are relevant to the firm, it includes also the innovation that exists but not currently in use by the firm (Baker, 2011), the characteristics inherent in the technology solution (Al Hadwer, 2021), the technology's relative advantage over existing technological solutions, compatibility with current solutions and processes, complexity, security features (Prakash, 2025), information technology maturity (Yeh et al., 2015), technological competence (Ng et al., 2022), technology perceived costs and benefits (Lin, 2014), and data quality (Khurshid et al., 2024).

The organization dimension includes the characteristics and resources of the firm, structures between employees, inter-firm communication, size of the firm, the slack resources (Baker, 2011), top management support (Lin, 2014; Yeh et al., 2015), absorptive capacity (Lin, 2014), organizational learning capabilities (Malik et al., 2021), need for transparency (Khurshid et al., 2024), financial resources (Alsehani et al., 2024), organizational innovativeness, and organizational culture (Prakash, 2025).

The environment dimension includes the external factors such as the structure of the industry, the existence or absence of technology providers, the regulatory landscape (Baker, 2011), competitive pressure and partnership quality (Lin 2014; Yeh et al., 2015), standards uncertainty (Malik et al., 2021), government support (Ng et al., 2022), civil society participation (Khurshid et al., 2024), privacy and trust (Alsehani et al., 2024), industry trends, and consumer readiness (Prakash, 2025).

TOE in the Public Sector

In the public sector, there has been a growing interest in applying the TOE framework to understand technology adoption. Studies have examined diverse context, including the factors motivating Malaysian government to utilize chatbots (Jais et al., 2024), adoption of software-as-a-service in public sector organizations (Kilani, 2022), civil service managers' attitudes toward administrative innovations (Basloom et al., 2022), open government data intention-adoption (Khurshid et al., 2024), and the adoption of social media tools in government organizations (Alsehani et al., 2024).

Findings across these studies suggest that the influence of the three TOE dimensions varies across settings. For instance, Neumann et al. (2024), using Swiss case studies, highlighted that the technology and organizational factors were less critical than environmental ones in shaping AI processes. By contrast, Jais et al. (2024) found that the technological readiness, organizational readiness and organizational learning capabilities positively influenced the intention to adopt chatbots in the Malaysian government. Other research notes that all three dimensions are influential for the social media adoption by government organization in Saudi Arabia (Alsehani et al., 2024), and support local government adoption of technologies for citizen participation (Adade & de Vries, 2024). Together, these findings indicate that the balance of influence among TOE dimensions is context-specific but that the framework remains a robust lens for analyzing public sector technology adoption.

The public sector context also presents differences compared to private organizations. Governments tend to minimize risk, which shapes the role of each dimension differently. For the technological dimension, public agencies often rely on external partners to

support AI-enabled transformation initiatives. For the organizational dimension, long employee tenure and limited external experience may slow change processes. For the environmental dimension, governments face less uncertainty when scanning their external environment, since many initiatives and applications are publicly visible and subject to transparency requirements (Desouza et al., 2020).

Extended TOE framework: The Technology Organizations-Environment Governance (TOEG) framework

The unique features of the public sector, particularly the importance of regulation, accountability, and legitimacy, suggest that governance may play a distinct role beyond the three original TOE dimensions. This highlights the need to extend the framework when applied to national-level AI adoption.

The implementation of AI in the public sector introduces a host of governance challenges, including transparency, accountability, privacy, data quality and value judgement concerns (Chen et al., 2023). These issues increase the need for robust governance frameworks, which can guide and shape the use of AI by governments to achieve desired outcomes (Henman, 2020). At the country level, governance encompasses macro-level factors such as economic, legal, and financial development, control mechanisms accountability, political stability corruption control, and the effective, transparent, and inclusive administration of public resources (Hillier et al., 2011; Groșanu et al., 2015; Umeanwe et al., 2025). Evidence shows that governance plays a critical role in the public sector digital transformation. Case studies from Australia, Denmark, and the Republic of Korea highlight how governance vision, strategies, and institutional frameworks directly support successful transformation initiatives (Meyerhoff Nielsen, 2019). These are crucial

to overcome the barriers to change associated with the transformation initiatives (Ndou, 2004).

Beyond the public sector, governance has been shown to influence a wide range of outcomes: business environments and entrepreneurship (Groşanu et al., 2015), innovation processes (Sivak et al., 2011), and public perceptions of AI (Vu et al., 2022). Country-level governance also affects firms' performance and economic development—for example, shaping cross-border acquisitions (Ellis et al., 2017), profit-shifting behavior (Sugathan & George, 2015), R&D investment (Hillier et al., 2011), labor productivity (Cosset et al., 2016), use of financial instruments (Lel, 2012), and foreign direct investment flows (Filippaios et al., 2019). These findings underline governance as a systemic factor that conditions innovation and adoption, making it highly relevant for AI implementation in government.

Recent studies confirm that governance characteristics, such as regulatory quality, political stability, and corruption control, directly affect AI readiness (Socol & Iuga, 2024; Shonhe et al., 2024). Yet readiness alone does not ensure implementation. Gaps in governance, along with infrastructure and human capital deficits, help explain why countries fail to move from readiness to deployment. As governments increasingly apply AI to service delivery, policy-making, and internal management (Van Noordt et al., 2022; Chen et al., 2021), governance emerges as both an enabler and a potential barrier.

The flexibility of the TOE framework has led scholars to extend it with new dimensions such as perceived risk (Malik et al., 2021), sustainability (Satyro et al., 2024), transformational leadership (Sihotang et al., 2024), and cybersecurity concerns (Wallace et al., 2020). However, governance, despite its centrality to digital transformation, has

received little systematic attention within TOE studies. Therefore, we propose extending the TOE framework by adding governance as a fourth dimension, creating the TOE-G framework (see Figure 2). This extension offers a more comprehensive lens for analyzing AI implementation at the national level, where institutional quality, regulatory capacity, and political stability play pivotal roles alongside technological, organizational, and environmental factors.

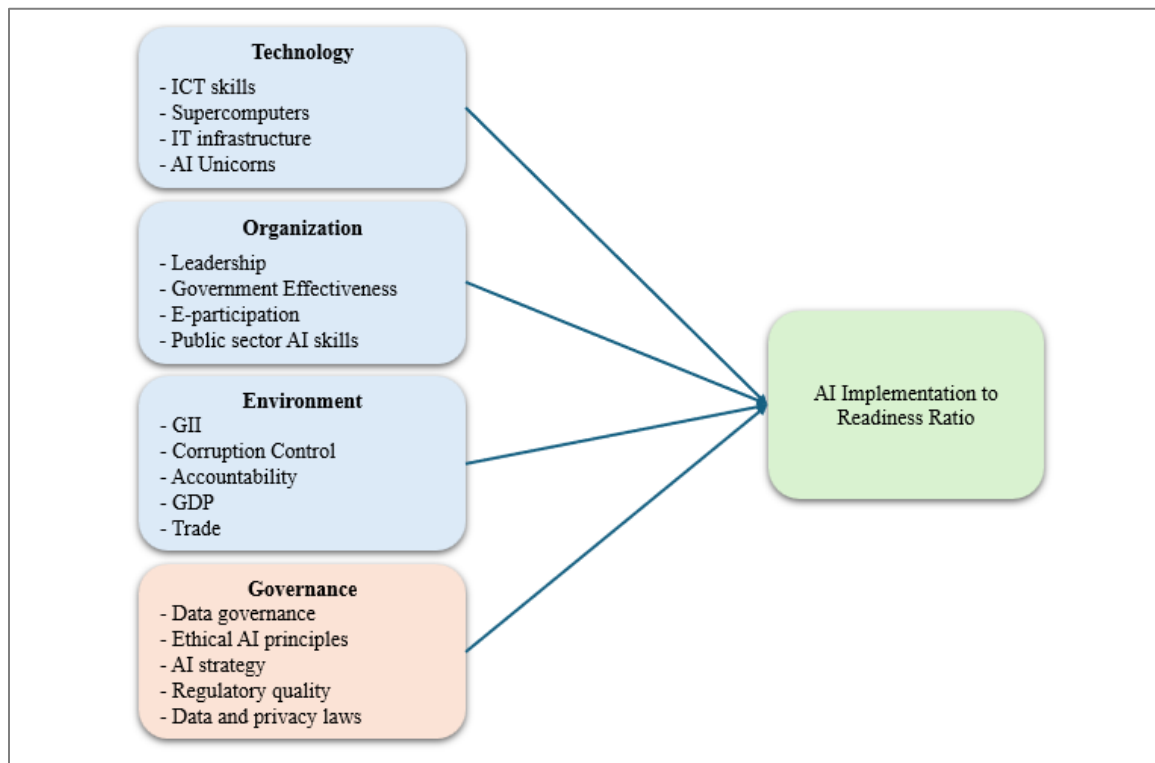


Figure 2. The TOE-G framework.

Methodology

Data

To answer the research question, we compiled a cross-country dataset covering 77 countries in 2024. The dependent variable, AI implementation relative to readiness, was

derived from two internationally recognized benchmarks: the Global AI Index (Tortoise Media, 2024) and the AI Readiness Index (Oxford Insights, 2024). Independent variables were drawn from the UN E-Government Survey (2024), the World Bank Worldwide Governance Indicators, and the Global Innovation Index (2024), allowing us to operationalize the three TOE dimensions as well as the governance dimension. A detailed overview of variables is provided in Table 1.

The Global AI Index ranks countries based on AI implementation, innovation, and investment. The implementation indicators reflect the availability of structures and practitioners needed to operationalize AI within the country, it includes sub-indicators of talent, infrastructure and operating environment, the innovation indicators reflect technology breakthroughs and advancements in methodology that are indicative of greater capacity for artificial intelligence in the future. This pillar contains the sub-indicators of research and development, and the investment indicators reflect financial and procedural commitments to artificial intelligence. This pillar contains the sub-pillars of the commercial ecosystem and government strategy (Tortoise Media, 2024).

The AI readiness index assesses governments' preparedness to adopt AI across three core pillars: government capacity, technology sector, and data and infrastructure. It highlights progress, identifies gaps, and provides actionable insights for policymakers striving to integrate AI into public service delivery. The government pillar includes indicators related to the strategic vision developing and governing AI, supported by appropriate regulation and attention to ethical risks, internal digital capacity, and the adaptability in the face of new technologies. The technology pillar includes the supply of AI tools and resources to support governments in responding to their evolving needs, and the data. The

infrastructure pillar reflects the extent to which countries possess high-quality, representative data and the supporting systems required to operationalize AI in public service delivery (Oxford Insights, 2024).

Measures

Our dependent variable, AI implementation relative to readiness, is measured with a continuous variable that is calculated by dividing the implementation score (Global AI index) by its readiness score (AI Readiness Index). To operationalize the independent variables, we applied principal component analysis (PCA) to aggregate multiple indicators into composite measures for each TOE-G dimension, thereby reducing multicollinearity and capturing the most relevant variance. The technology dimension is represented by ICT skills, IT infrastructure maturity, the number of AI unicorns, and supercomputing capacity. The organizational dimension includes government effectiveness, public sector AI skills development, leadership capacity, and e-participation. The environmental dimension covers control of corruption, accountability, GDP (log), trade openness (log), and the Global Innovation Index. Finally, the governance dimension incorporates data protection and privacy laws, regulatory quality, adoption of ethical AI principles, the presence of a national AI strategy, and data governance frameworks. Full details on variable definitions, measurement types, and sources are presented in Table 1.

Table 1: Variables Description

TOE Dimension	Variable Name	Variable Description	Type	Source
Dependent Variable	Implementation to readiness ratio	Ratio of AI implementation level to AI readiness level	Continuous	-
Technology	ICT skills	Level of ICT skills in the population based on WEF Executive Opinion Survey	Continuous	2024 Government AI Readiness Index
Technology	Supercomputers	Log-transformed count of supercomputers based on TOP500.org data	Continuous	2024 Government AI Readiness Index
Technology	IT infrastructure	Govtech Maturity Index Core Government Systems score	Continuous	2024 Government AI Readiness Index
Technology	AI Unicorns	Number of AI Unicorns (Private companies with a valuation over \$1 billion) log transformation from CB insights	Continuous	2024 Government AI Readiness Index
Organization	Leadership	The country's leadership and foresight score	Continuous	Country Rankings - CGGI
Organization	Government Effectiveness	captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures from WGI indicators	Continuous	2024 Government AI Readiness Index
Organization	E-participation	the effectiveness and relevance of the digital information and services offered by Governments to encourage citizen engagement in public policy formulation	Continuous	2024 UN E-Government Survey 2024
Organization	Public sector AI skills	Measures steps countries have taken to support skills development in relation to responsible AI within the civil service and judiciary according to the Global Index on Responsible AI	Continuous	2024 Government AI Readiness Index
Environment	GII	Global Innovation Index	Continuous	Global Innovation Index 2024 - GII 2024 results
Environment	Corruption Control	Country rank in the corruption control according WGI	Continuous	Worldwide Governance Indicators DataBank

TOE Dimension	Variable Name	Variable Description	Type	Source
Environment	Accountability	Accountability ranking per WGI	Continuous	2024 Government AI Readiness Index
Environment	GDP	GDP per capita	Continuous	GDP per capita - Countries - List World"
Environment	Trade	Trade (% of GDP)	Continuous	World Bank
Governance	Data governance	Data governance according to desk research (with support from the GovTech Maturity Index I-34)	Continuous	2024 Government AI Readiness Index
Governance	Ethical AI principles	Adoption of OECD AI Principles or independent frameworks aligned with OECD values through desk research	Binary	2024 Government AI Readiness Index
Governance	AI strategy	The National AI Strategy for the country through desk research	Binary	2024 Government AI Readiness Index
Governance	Regulatory quality	Regulation quality ranking per WGI indicators	Continuous	2024 Government AI Readiness Index
Governance	Data and privacy laws	Data protection and privacy laws identified through desk research	Continuous	2024 Government AI Readiness Index

Model

We employed beta regression because the dependent variable, AI implementation relative to readiness, is continuous and bounded between 0 to 1, inclusive. Unlike OLS, which can generate predictions outside the feasible range, or fractional logit models, which assume a specific distribution, beta regression is well suited for proportional outcomes as

it allows flexible distributional shapes and constrains predictions within the (0,1) interval (Ferrari & Cribari-Neto, 2004).⁶

We estimated 12 beta-regression model specifications for the dependent variable y_i = country's implementation to readiness ratio ($0 < y_i < 1$). The baseline specification (Model 1) includes the main effects of the four TOE-G dimensions. Models 2–6 introduce quadratic terms to capture possible nonlinear relationships, while Models 7–12 test pairwise interactions to examine complementarities and trade-offs among dimensions.

To verify the robustness of the results, we re-estimated the models using Generalized Linear Models (GLM) with a logit link, and ordinary least squares (OLS) regression. These results were consistent in both direction and significance, reinforcing the reliability of our main results through beta regression. Please refer to Appendix 4 A for detailed robustness check results.

Model.	Description	Equation
1	Main effects of Technology, Organization, Environment, Governance	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Org}_i + \beta_3 \text{Env}_i + \beta_4 \text{Gov}_i$
2	Quadratic terms of all the four variables	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Tech}_i^2 + \beta_3 \text{Org}_i + \beta_4 \text{Org}_i^2 + \beta_5 \text{Env}_i + \beta_6 \text{Env}_i^2 + \beta_7 \text{Gov}_i + \beta_8 \text{Gov}_i^2$
3	Quadratic term for the Tech only	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Tech}_i^2 + \beta_3 \text{Org}_i + \beta_4 \text{Env}_i + \beta_5 \text{Gov}_i$
4	Quadratic term for the Org only	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Org}_i + \beta_3 \text{Org}_i^2 + \beta_4 \text{Env}_i + \beta_5 \text{Gov}_i$
5	Quadratic term for the Env only	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Org}_i + \beta_3 \text{Env}_i + \beta_4 \text{Env}_i^2 + \beta_5 \text{Gov}_i$
6	Quadratic term for the Gov only	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Org}_i + \beta_3 \text{Env}_i + \beta_4 \text{Gov}_i + \beta_5 \text{Gov}_i^2$
7	Interaction between Tech & Org	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Org}_i + \beta_3 \text{Env}_i + \beta_4 \text{Gov}_i + \beta_5 (\text{Tech}_i \times \text{Org}_i)$

⁶ To avoid boundary issues where observations equal exactly 0 or 1, the dependent variable was transformed following standard practice: $\text{Dependent Variable} = ((\text{Dependent Variable} * 78) + 0.5) / 77$, where 77 is the sample size. This ensures all values lie strictly within (0,1).

8	Interaction between Tech & Env	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Org}_i + \beta_3 \text{Env}_i + \beta_4 \text{Gov}_i + \beta_5 (\text{Tech}_i \times \text{Env}_i)$
9	Interaction between Tech & Gov	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Org}_i + \beta_3 \text{Env}_i + \beta_4 \text{Gov}_i + \beta_5 (\text{Tech}_i \times \text{Gov}_i)$
10	Interaction between Org & Env	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Org}_i + \beta_3 \text{Env}_i + \beta_4 \text{Gov}_i + \beta_5 (\text{Org}_i \times \text{Env}_i)$
11	Interaction between Org & Gov	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Org}_i + \beta_3 \text{Env}_i + \beta_4 \text{Gov}_i + \beta_5 (\text{Org}_i \times \text{Gov}_i)$
12	Interaction between Env & Gov	$y_i = \beta_0 + \beta_1 \text{Tech}_i + \beta_2 \text{Org}_i + \beta_3 \text{Env}_i + \beta_4 \text{Gov}_i + \beta_5 (\text{Env}_i \times \text{Gov}_i)$

Results

Descriptive Statistics

Table 2 presents descriptive statistics for the variables included in the principal component analysis. Most of the indicators range between 0 and 100, reflecting normalized scores of country-level performance across different dimensions. Exceptions are GDP, which is presented in logarithmic form, and trade, which is expressed as a percentage of GDP. The dependent variable (AI implementation-to-readiness ratio) has a mean of 0.24 and a standard deviation of 0.16, with values ranging from 0.006 to 0.994. This widespread indicates substantial variation among countries in their ability to translate AI readiness into actual implementation. Some countries achieve close to parity between readiness and implementation, while others display near-zero conversion, highlighting the existence of the readiness–implementation gap.

Table 2: Descriptive Statistics

Category	Variable	Mean	SD	p25	p75	Min	Max
Dependent Variable	AI implementation to readiness ratio	0.243315	0.1579	0.169404	0.267138	0.006329	0.993671
Technology	IT infrastructure	75.46314	14.86091	68.34764	84.12017	14.16309	100

	ICT skills	61.08992	17.22021	48.653	74.10139	19.57762	100
	AI Unicorns	5.129338	15.58015	0	0	0	100
	Supercomputers	17.3785	23.06725	0	31.23126	0	100
Organization	Government Effectiveness	61.99399	17.94146	46.14838	75.88864	20.19826	100
	Public sector AI skills	36.48368	27.3569	16.02868	50.11583	0	100
	Leadership	60.19429	29.27216	35.5566	85.99056	1	100
	E-participation	70.81248	21.88226	59.82184	88.52052	1	100
Environment	corruption control	61.21328	26.81954	38.20755	83.96227	8.490566	100
	Accountability	60.40394	26.95004	38.08212	84.08627	10.34577	100
	GDP	9.512283	1.219097	8.458928	10.63886	6.791222	11.57117
	Trade (% of GDP)	4.40158	0.613628	3.927605	4.850221	3.025204	6.002549
	GII	64.60292	24.53915	49.73846	84.00769	1	100
Governance	Data and privacy laws	97.46835	13.63145	100	100	0	100
	Regulatory quality	62.10822	19.06948	46.71522	78.50616	19.79341	100
	Ethical AI principles	77.21519	42.21243	100	100	0	100
	AI strategy	83.5443	35.55559	100	100	0	100
	Data governance	75.94937	32.63115	75	100	0	100

Regression Results: Dimension-Level Analysis

Table 3 presents the beta regression estimates for the four TOE-G dimensions across twelve model specifications. Technology emerges as the strongest and most consistent predictor. In the baseline model, technology has a positive and highly significant effect ($\beta = 0.437$, $p < 0.01$). This result holds across all specifications, with coefficients ranging between $\beta = 0.331$ ($p < 0.01$, Model 9) and $\beta = 0.454$ ($p < 0.01$, Model 8). In the quadratic specification, the squared technology term is also significant and positive ($\beta = 0.025$, $p < 0.05$ in Model 2; $\beta = 0.021$, $p < 0.1$ in Model 3), indicating increasing marginal returns: countries with stronger technological ecosystems derive disproportionately greater implementation benefits.

The organizational dimension is consistently insignificant across most models (e.g., $\beta = -0.075$, $p = \text{n.s.}$, baseline model). However, interaction effects show nuance. Model 11 indicates that the interaction between organization and governance is positive and significant ($\beta = 0.075$, $p < 0.01$), meaning that organizational strength mitigates the negative influence of governance. By contrast, interactions such as technology $\times$ governance ($\beta = 0.094$, $p = \text{n.s.}$, Model 9) and environment $\times$ governance ($\beta = -0.020$, $p = \text{n.s.}$, Model 12) are not significant, suggesting that only organizational capacity plays a buffering role.

The environment dimension is generally positive and significant, with coefficients ranging from $\beta = 0.163$ ($p < 0.05$, Model 9) to $\beta = 0.213$ ($p < 0.01$, Model 3). However, its quadratic term becomes negative ($\beta = -0.035$, $p < 0.1$ in Model 2; $\beta = -0.023$, ns in Model 5), suggesting diminishing returns. In practical terms, improvements in innovation, trade, and corruption control foster implementation up to a point, but at very high levels the relationship weakens or reverses.

Governance shows the most complex pattern. In the baseline model, governance has a strong negative effect ($\beta = -0.435$, $p < 0.01$), and remains negative and significant in nearly all specifications, with coefficients ranging from $\beta = -0.291$ ($p < 0.01$, Model 9) to $\beta = -0.465$ ($p < 0.01$, Model 12). However, when quadratic terms are introduced, the squared governance term is positive and significant ($\beta = 0.081$, $p < 0.01$ in Model 2; $\beta = 0.076$, $p < 0.01$ in Model 6). This indicates a curvilinear effect: at moderate levels, governance may constrain implementation, but beyond a threshold, certain governance features (such as stronger regulatory quality) can begin to support adoption.

Regression Results: Variable-Level Analysis

Table 4 disaggregates the four dimensions to identify which factors drive the observed patterns. Within the technology dimension, AI unicorns have a positive and highly significant effect ($\beta = 0.019$, $p < 0.01$, Model 1), highlighting the importance of entrepreneurial ecosystems. In the full specification, however, the coefficient turns negative ($\beta = -0.006$, $p < 0.01$, Model 5), suggesting potential crowding-out effects or multicollinearity when other factors are included. IT infrastructure is insignificant in dimension-only models but becomes positive and significant in the full model ($\beta = 0.003$, $p < 0.05$), underlining its foundational role once other influences are controlled. ICT skills and supercomputers are consistently insignificant.

In the environment dimension, innovation capacity has a strong and consistent positive impact ($\beta = 0.035$, $p < 0.01$, Model 3). By contrast, accountability exerts a negative effect ($\beta = -0.010$, $p < 0.01$, Model 3), and trade openness also negatively influences implementation ($\beta = -0.638$, $p < 0.01$, Model 3). These findings imply that while innovation ecosystems propel adoption, procedural accountability requirements and exposure to global trade dynamics may delay or complicate AI deployment.

For the organizational dimension, government effectiveness is surprisingly negative ($\beta = -0.025$, $p < 0.05$, Model 2), implying that traditional bureaucratic efficiency may hinder rather than facilitate disruptive AI adoption. Public sector AI skills are positive and marginally significant ($\beta = 0.008$, $p < 0.1$, Model 2), while leadership shows a strong positive effect in the dimension-only model ($\beta = 0.015$, $p < 0.05$) but turns negative in the full specification ($\beta = -0.002$, $p < 0.1$), again pointing to possible tensions between visionary leadership and regulatory or institutional constraints. E-participation is

insignificant in early models but positive in the full specification ($\beta = 0.002$, $p < 0.1$), suggesting a role for citizen engagement in enabling implementation once broader conditions are accounted for.

Governance effects are highly differentiated. Data protection and privacy laws show a strong negative effect ($\beta = -0.025$, $p < 0.01$, Model 4), while ethical AI principles are positive ($\beta = 0.005$, $p < 0.05$). Regulatory quality becomes significant in the full specification ($\beta = 0.007$, $p < 0.05$), and adoption of a national AI strategy is unexpectedly negative ($\beta = -0.001$, $p < 0.1$). These results highlight the dual role of governance: while clear ethical guidelines and regulatory quality support adoption, extensive legal frameworks and formal strategies may inadvertently slow implementation.

Table 3: Regression Results for the TOEG Dimensions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
tech	0.437*** (0.032)	0.249*** (0.069)	0.321*** (0.078)	0.431*** (0.029)	0.429*** (0.032)	0.406*** (0.031)	0.352*** (0.085)	0.454*** (0.042)	0.331*** (0.090)	0.438*** (0.033)	0.403*** (0.032)	0.438*** (0.032)
org	-0.075 (0.085)	-0.056 (0.058)	-0.060 (0.084)	-0.074 (0.083)	-0.054 (0.082)	-0.112 (0.070)	-0.055 (0.083)	-0.076 (0.084)	-0.080 (0.082)	-0.071 (0.086)	-0.072 (0.084)	-0.057 (0.085)
env	0.203** (0.080)	0.009 (0.051)	0.213*** (0.079)	0.202** (0.080)	0.181** (0.073)	0.041 (0.062)	0.199** (0.080)	0.203** (0.080)	0.163** (0.075)	0.199** (0.078)	0.140* (0.074)	0.197*** (0.075)
gov	-0.435*** (0.087)	0.039 (0.079)	-0.413*** (0.087)	-0.428*** (0.089)	-0.437*** (0.082)	-0.007 (0.086)	-0.408*** (0.086)	-0.444*** (0.088)	-0.291*** (0.106)	-0.440*** (0.086)	-0.273*** (0.084)	-0.465*** (0.095)
tech ²		0.025** (0.011)	0.021* (0.011)									
org ²		0.005 (0.033)		0.012 (0.026)								
env ²		-0.035* (0.019)			-0.023 (0.016)							
gov ²		0.081*** (0.014)				0.076*** (0.015)						
tech * org							0.042 (0.037)					
tech * env								-0.019 (0.023)				
tech * gov									0.094 (0.062)			
org * env										-0.017 (0.022)		
org * gov											0.075*** (0.025)	
env * gov												-0.020 (0.023)
Constant	-1.344*** (0.055)	-1.480*** (0.080)	-1.374*** (0.054)	-1.373*** (0.080)	-1.266*** (0.072)	-1.539*** (0.069)	-1.395*** (0.061)	-1.322*** (0.052)	-1.438*** (0.077)	-1.301*** (0.069)	-1.484*** (0.067)	-1.304*** (0.070)
scale												
Constant	2.738*** (0.254)	3.241*** (0.304)	2.764*** (0.276)	2.742*** (0.255)	2.758*** (0.261)	3.108*** (0.245)	2.757*** (0.272)	2.746*** (0.249)	2.809*** (0.277)	2.743*** (0.255)	2.842*** (0.259)	2.745*** (0.257)

Observations	77	77	77	77	77	77	77	77	77	77	77	77
R-sq.												

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regression Results for the factors within each dimension

	(1)	(2)	(3)	(4)	(5)
IT infrastructure	-0.022 (0.015)				0.003** (0.001)
ICT skills	0.002 (0.004)				0.000 (0.001)
AI Unicorns	0.019*** (0.005)				-0.006*** (0.002)
Supercomputers	0.004 (0.004)				0.001 (0.001)
Government Effectiveness		-0.025** (0.010)			-0.002 (0.002)
Public sector AI skills		0.008* (0.004)			0.001 (0.001)
Leadership		0.015** (0.006)			-0.002* (0.001)
E-participation		0.000 (0.006)			0.002* (0.001)
corruption control			-0.007 (0.006)		-0.000 (0.002)
Accountability			-0.010*** (0.003)		-0.000 (0.002)
GDP			-0.002 (0.163)		-0.016 (0.026)
Trade (% of GDP)			-0.638***		0.004

			(0.224)		(0.056)
GII			0.035***		-0.001
			(0.006)		(0.002)
Data and privacy laws				-0.025***	-0.003
				(0.004)	(0.002)
Regulatory quality				0.003	0.007**
				(0.004)	(0.003)
Ethical AI principles				0.005**	0.001
				(0.002)	(0.001)
AI strategy				-0.003	-0.001*
				(0.002)	(0.001)
Data governance				-0.000	0.000
				(0.002)	(0.001)
Constant	0.133	-0.807*	0.248	0.982***	-2.571***
	(1.241)	(0.435)	(1.045)	(0.294)	(0.387)
scale					
Constant	2.248***	1.769***	2.447***	1.928***	5.267***
	(0.338)	(0.331)	(0.270)	(0.536)	(0.489)
Observations	77	77	77	77	77
R-sq.					

Discussion

This paper extends the TOE framework by introducing governance as a fourth dimension shaping national AI adoption and highlights the differential role of technology, environment, and governance in driving implementation. It addresses the puzzle of why many countries lag behind in actual AI implementation despite high readiness scores, showing that weak technological infrastructure, limited digital skills, lack of support for AI entrepreneurship, and adverse environmental conditions such as corruption, accountability deficits and low trade openness constrain implementation. More strikingly, the results suggest that governance, typically assumed to facilitate innovation, can, under certain conditions, hinder AI deployment.

The importance of technology as a driver of AI implementation is consistent with earlier findings at the organizational level (Cubric, 2020). Studies have shown that IT infrastructure is critical for production systems (Merhi et al., 2024), digital skills accelerate the adoption in human resources management (Madanchian et al., 2025), and overall IT capacity underpins AI adoption in SMEs (Arroyabe, 2024). Our findings confirm this consensus while scaling it to the national level, reinforcing that foundational digital capabilities remain indispensable for countries seeking to move from readiness to real-world AI use.

The external environment also plays a significant role, aligning with prior work linking economic institutions and macroeconomic stability to innovation. Higher GDP per capita, trade openness, and competitiveness tend to foster adoption, while high corruption and accountability challenges raise the costs of innovation and reduce incentives for

technological investment (Gelebo et al., 2015; Hooks et al., 2022). These findings support broader evidence that growth, institutional quality, and macroeconomic stability sustain long-run innovation (Pradhan et al., 2017; Jafarnejad et al., 2013).

The most unexpected finding concerns governance. While previous studies consistently emphasize its positive role in fostering entrepreneurship, innovation, and public trust (Groșanu et al., 2015; Sivak et al., 2011; Vu et al., 2022), our results suggest a more complex and at times counterintuitive relationship: extensive governance frameworks can actually impede AI implementation. One plausible explanation lies in overregulation. As governments design multiple strategies, principles, and oversight mechanisms for AI, the policy landscape becomes fragmented, overlapping, and difficult to navigate. This can slow down bureaucratic decision-making, create uncertainty for public administrators and private innovators, and ultimately discourage risk-taking. Moreover, a proliferation of governance frameworks can shift resources away from experimentation and operationalization toward compliance and reporting, delaying the move from readiness to real-world deployment.

The contrast between the European Union and the United States illustrates this dynamic vividly. The EU has positioned itself as a global leader in normative AI governance, exemplified by the forthcoming AI Act, which introduces comprehensive rules on transparency, risk classification, and accountability. While such frameworks demonstrate strong commitment to ethical and responsible AI, they also introduce layers of legal and procedural hurdles that slow down implementation. By contrast, the United States leads the world in AI deployment without a unified federal strategy or comprehensive regulation. Instead, its governance regime is fragmented across state-level laws, sector-

specific guidelines, and nonbinding federal principles. This lighter, more flexible approach has enabled faster experimentation and scaling, even if it raises concerns about consistency and equity (World Bank, 2024). Taken together, these cases suggest that the effectiveness of governance is less about the quantity of rules and more about their design, coherence, and fit with the country's absorptive capacity and institutional legitimacy. In contexts where institutions are strong and trusted, governance can support innovation; where they are rigid or fragmented, governance can unintentionally hold it back.

This interpretation aligns with longstanding debates in the innovation literature about the costs of bureaucracy and excessive regulation. Research has shown that burdensome procedures and rigid oversight mechanisms can stifle entrepreneurship (Worku, 2016), reduce firms' capacity to innovate (Henrekson, 2014), and in some cases push new ventures toward failure (Edoho, 2015). In the context of rapidly evolving technologies like AI, scholars have also observed that regulation often lags behind innovation cycles, creating a mismatch that hinders adoption (Trubnikov, 2017). In such cases, governance acts as a brake, discouraging investment and experimentation precisely when flexibility and speed are most needed.

At the same time, not all regulations are detrimental. Some studies argue that governance exerts a U-shaped influence on technology adoption: restrictive in the early stages, but ultimately enabling once absorptive capacity, institutional trust, and regulatory expertise mature (Ai et al., 2021). In this view, governance initially slows down implementation by imposing constraints and costs, but as institutions stabilize and align with technological change, regulation provides clarity, reduces uncertainty, and fosters trust among

stakeholders. Our findings resonate with the “negative” side of this debate, showing empirically that at the country level, more governance frameworks do not necessarily equate to greater AI implementation. Instead, the effectiveness of governance depends on timing, design, and institutional maturity. These insights invite a more nuanced understanding of governance in national AI ecosystems: neither wholly enabling nor wholly constraining, but contingent on broader political and institutional conditions.

This research has several theoretical implications. First, it contributes to the growing literature of smart government and AI, by shifting attention from readiness to the actual implementation. By analyzing why many countries fail to translate readiness into deployment, it offers new insights into how nations move from potential to practice. Second, it extends the TOE framework by incorporating governance as a distinct dimension, thereby advancing the TOE-G framework. This extension enriches theory by acknowledging that governance factors, such as regulatory quality, data governance, ethical principles, and AI national strategies, play a pivotal role in shaping outcomes, though not always in the expected positive direction. Third, this research offers cross-national empirical evidence on AI implementation, helping to address the scarcity of comparative studies in this domain. Finally, by confirming the enduring importance of the technology and environment dimensions alongside governance, the study offers a more comprehensive framework for understanding how multiple, interacting forces shape AI implementation at the country level.

This research provides several practical implications for policymakers. First, it highlights the importance of balance in governance: while regulations and frameworks are essential to ensure trust and accountability, excessive or overlapping governance can slow

implementation, leaving countries highly “ready” but unable to translate this readiness into action. Policymakers should therefore aim for governance that safeguards rights without stifling innovation. Second, the findings emphasize the importance of investing in technology enablers such as infrastructure and digital skills, but also of strengthening macro-environmental conditions, including corruption control, accountability, and openness to trade. This integrated perspective highlights that AI adoption cannot succeed in isolation from broader institutional and economic contexts. Finally, the study shows that strategies must be context sensitive. Developed countries may need to avoid overregulation that hinders experimentation, while developing countries often face more fundamental challenges such as weak institutions, limited infrastructure, and shortages of expertise. Recognizing these different conditions allows policymakers to design AI ecosystems tailored to their context, balancing governance, technology, and environmental factors in ways that accelerate sustainable and effective implementation.

Conclusion

This research examined why some countries succeed in moving from AI readiness to actual AI implementation while others lag behind, despite appearing well-prepared. Drawing from publicly available data from AI Readiness Index and the Global AI Index and extending the TOE framework with a governance dimension (TOE-G), the study provides new insights into the drivers of AI-enabled smart government. The findings highlight that technology and environment factors play a positive role in fostering implementation, whereas governance exerts a negative influence, suggesting that investing heavily in regulatory frameworks may inadvertently slow progress. The

organization dimension, meanwhile, proved largely insignificant on its own but gained importance when interacting with governance.

These findings contribute to both theory and practice by shedding light on the conditions under which readiness translates (or fails to translate) into actual implementation. At the same time, the study has several limitations. First, the analysis relies on secondary global indices, which might not fully capture country-specific contextual factors. Second, its cross-sectional design cannot address how implementation evolves over time. Third, the scope of variables within each dimension was limited by data availability. Future research could therefore employ longitudinal approaches to trace the changes in AI implementation trajectories, complement global indices with primary data collected directly from government agencies, and expand the range of variables within the TOE-G framework to deepen understanding of national differences.

Chapter 5: Conclusion

The main objective of this thesis is to develop a deeper understanding of the factors impacting the digital transformation in the public sector in its various forms; e-government-m-government and smart government, with a particular emphasis on the factors that impact citizens' adoption of e-government and m-government, as well as the gap between AI readiness and AI implementation, focusing on the AI as an enabler for smart government. To achieve this purpose, each of the previous three chapters in this thesis reviewed the relevant literature, identified critical gaps, formulated research questions, and empirically examined them using different methodological approaches.

The analysis conducted revealed that external rewards significantly increase citizens' likelihood of e-government adoption when moderated by demographics and digital skills, further, it shows that m-government app improvements and positive media framing enhance the citizens' sentiment, while mandatory adoption raises resistance, and investigated why countries lag behind AI implementation despite their AI readiness and identified how excessive governance may negatively affect the progress.

The thesis offered theoretical contribution to the growing body of literature in the digital transformation of the public sector, extended the UTAUT model to include external rewards as an extrinsic motivator, proposed an extended TOE-G framework that incorporates governance alongside technology, organization, and environment, and provided methodological contribution by deploying four different analysis methods sentiment analysis, topic modeling, regression, and fsQCA to analyze citizens' sentiment and media frames.

The table below summarizes the objective of each paper, key findings, theoretical contributions, and policy implications:

Table 1: Papers Summary

Section	Focus / Objectives	Key Findings	Theoretical Contributions	Practical / Policy Implications
E-Government	Examine the role of extrinsic motivation (external rewards) on e-government adoption.	• External rewards positively influence adoption, especially for seniors, low-income, rural, and low-education groups. • Digital skills moderate this effect.	• Extended UTAUT model with extrinsic motivation. • Addressed developing country context and demand-side adoption. • Large-scale empirical validation.	• Offer external rewards/incentives. • Provide tech grants/subsidies to low-income groups. • Implement digital literacy/upskilling programs. • Focus on mobile-centric services for efficiency.
M-Government	Explore how app improvements, mandatory use, and media framing affect citizen sentiment.	• Positive media framing & app quality improve sentiment; mandatory use increases resistance. • Sentiment evolves across app phases. • Persistent technical issues remain.	• Links media framing theory to digital government. • Analyzes dynamic user sentiment (longitudinal). • Uses fsQCA to reveal multifactor interactions.	• Continuously improve app functionality. • Establish help desks & auto-support systems. • Conduct digital ID awareness/training. • Use review analysis for ongoing improvement.
Smart Government	Investigate AI readiness vs implementation gap using TOE-G framework.	• Technology & environment facilitate implementation. • Governance can hinder through overregulation. • Organizational role minimal unless interacting with governance.	• Extends TOE framework → TOE-G (adds governance). • Provides cross-country empirical evidence explaining readiness-implementation gap.	• Balance governance and avoid overregulation. • Invest in infrastructure & digital skills. • Tailor AI strategies to national contexts. • Strengthen institutional quality & trust.

In the following section, the main findings and theoretical and practical implications of each chapter are presented.

Overview of Main Findings and Implications

1. E-Government

The findings of this paper highlight the critical role that extrinsic motivation plays in shaping the landscape of e-government adoption. The results show that external rewards significantly and positively influence citizens' likelihood of embracing e-government services. The paper sheds light on how minority groups such as senior citizens, citizens living in rural areas, and those who are categorized as low-income households tend to adapt e-government services if the service was associated with an external reward, which indicates that the e-government services could be a mean for the relief of the financial and economic stress on those minorities.

This work also validates the impact of socioeconomic conditions such as age, low income, and rural location on e-government service adoption. The results show that different age groups exhibit distinct preferences, abilities, and demands for technologies. Furthermore, the urban-rural divide emerges as a crucial factor influencing e-government adoption in the presence of external rewards. The results found that citizens in rural areas may exhibit a positive response to external rewards in the context of e-government adoption, additionally, the interaction between external rewards and low-income unveils a significant positive relationship, indicating that citizens within economically disadvantaged groups are more likely to adopt e-government services when motivated by external rewards.

Further, positive effect of external rewards on the adoption of e-government services would be stronger for individuals with lower educational levels, The empirical results reveal that the moderation impact of education is indeed significant. Citizens with lower educational levels exhibit a stronger positive response to external rewards, suggesting that educational disparities play a crucial role in shaping the dynamics of e-government adoption, the analysis also revealed a significant moderation effect of digital skills on the relationship between external rewards and e-government adoption., indicating that citizens lacking digital skills demonstrate a heightened positive response to external rewards, indicating that the presence of rewards acts as a crucial motivational factor for overcoming the perceived challenges associated with digital technologies.

This paper extended the UTAUT model which has been empirically tested for two decades in different scenarios including different countries, information systems, and variables (Williams et al.,2015). Scholars called to explore the blue ocean area in the UTAUT and called for enhancements on the current predictors and moderators in the original model (Blut et al.,2021), therefore, extending the UTAUT model to include extrinsic motivation factor helps in providing more explanation to the technology adoption. The paper makes significant theoretical contributions to the literature on e-government services adoption. First, the research addresses the context of a developing country facing unique socio-economic challenges and addresses the unfortunate side of the divide, where the majority of literature addressed the e-government adoption in the Western context, Second, it addressed the demand side of e-government by focusing on the factors driving citizens' adoption of e-government services, since the supply of e-government services will not contribute to the digital transformation goals without

adequate adoption by citizens. Third, the research extended the UTAUT model to include external rewards as an extrinsic motivation factor and revealed its importance on the adoption of e-government by citizens, answering the call for researchers to further develop the model by adding new predictors (Blut et al.,2021). Finally, it contributes to the e-government literature with large-scale empirical evidence, testing the cause-and-effect relationship between variables providing more generalizable results.

Further, the paper provides several lessons for policymakers, first, the government should leverage external rewards to encourage citizens to adopt e-government services. Second, establish a mechanism for technology grants or subsidies for low-income households to enable them to acquire essential equipment, such as computers, laptops, and smartphones, which can reduce economic barriers and facilitate broader access. Third, establish digital inclusion curricula and implement comprehensive digital literacy and upskilling training programs, targeting disadvantaged communities in specific areas. Finally, governments should focus their efforts on mobile-centric applications, which in turn can help governments achieve their cost efficiency and resource optimization goals.

2. M-Government

The m-government research paper provides critical insights into how policymakers' actions—such as media framing, mandating app usage, and app development— shape citizen sentiment toward m-government applications. The trend analysis of the citizen sentiment across the different phases of the application revealed the dynamic relationship between technological improvements and user satisfaction. The initial release phase recorded the lowest sentiment scores, reflecting widespread user frustration due to functionality gaps, technical errors, and usability issues. The topic modeling analysis

revealed important concerns at each development stage of the m-government application, During the initial phase, negative sentiment was primarily associated with technical issues such as face recognition errors, registration difficulties, and password malfunctions. As the application progressed, new concerns emerged alongside improvements. The introduction of updates led to topics related to updating errors, inaccurate information, incomplete services, and uncertainty regarding digital identification and the replacement of physical documents. The presence of persistent concerns—such as slow app speed and login issues—across all development stages suggests that certain structural issues require sustained attention from policymakers and developers.

A key contribution of this paper is its analysis of the impact of mandatory adoption on user sentiment and expands the literature by showing that while mandating m-government services may drive initial adoption rates, it does not necessarily translate into positive user experiences or long-term engagement. Additionally, media framing was found to strongly influence citizen sentiment, demonstrating that news coverage can significantly shape public trust and perceptions of digital government services. Positive framing can enhance public confidence and drive adoption, while negative framing—particularly narratives emphasizing security flaws, inefficiencies, or enforcement policies—can amplify distrust and resistance. This study extends media framing research into the technology-oriented public sector domain, offering new evidence of its impact on m-government sentiment formation. Beyond traditional regression analysis, fsQCA provided deeper insights into the conditions that shape public sentiment toward m-government applications. This method revealed interactions between multiple factors,

such as usability, mandatory policies, and media representation, which collectively influence citizen perceptions.

This paper makes several contributions to the existing literature on m-government adoption, digital public services, and media framing. It extends research on user satisfaction in m-government by analyzing sentiment evolution over time, rather than treating adoption as a static outcome. It expands the literature on mandatory technology adoption by demonstrating its specific impact in an m-government context, reinforcing prior studies on user resistance to impose digital services. Additionally, it bridges media framing theory with digital government research by showing how news narratives significantly influence citizen engagement with m-government services. From a methodological perspective, it introduces an innovative approach in m-government research, combining four analytical methods and providing a richer understanding of the interactions between policy decisions, usability, and media perception. Furthermore, it demonstrates that feature expansion alone is insufficient for sustained positive sentiment, reinforcing the importance of usability improvements and communication strategies in m-government adoption.

Further, the findings of this paper offer important policy implications for improving m-government adoption and user satisfaction. Governments should focus on continuously improving the application functionalities and expanding the scope of services offered to enhance user experience. Establishing a dedicated help desk with automated support systems can provide ongoing technical assistance. Awareness campaigns and training programs for government entities on how to verify the citizen identity digitally and how the digital ID can be used as a replacement of the physical documents are essential.

Additionally, governments should periodically analyze the m-government application reviews to uncover insights hidden in the citizens' comments and explore further areas for continued development.

3. Smart Government

The smart government paper examined how technology, organization, environment, and governance factors influence the translation of readiness into implementation, and addressed the question of why many countries lag behind in actual AI implementation despite high readiness scores, showing that weak technological infrastructure, limited digital skills, lack of support for AI entrepreneurship, and adverse environmental conditions such as corruption, accountability deficits and low trade openness constrain implementation. More strikingly, the results suggest that governance, typically assumed to facilitate innovation, can, under certain conditions, hinder AI deployment.

The results show that technology and environmental factors facilitate AI implementation, whereas governance exerts a negative effect, suggesting that overregulation and fragmented governance frameworks may delay adoption. The organizational dimension is largely insignificant, except when interacting with governance. It contributes to theory and practice in several ways. First, it advances theory by extending the TOE framework with governance as a critical dimension, thereby offering the TOE-G framework, second it provides novel cross-country empirical evidence on why AI readiness does not automatically translate into implementation and third, it offers practical guidance for policymakers seeking to close the readiness–implementation gap.

This paper has several theoretical implications. First, it contributes to the growing literature of smart government and AI, by shifting attention from readiness to the actual

implementation. Second, it extends the TOE framework by incorporating governance as a distinct dimension, thereby advancing the TOE-G framework. This extension enriches theory by acknowledging that governance factors, such as regulatory quality, data governance, ethical principles, and AI national strategies, play a pivotal role in in shaping outcomes. Third, this research offers cross-national empirical evidence on AI implementation, helping to address the scarcity of comparative studies in this domain. Finally, by confirming the enduring importance of the technology and environment dimensions alongside governance, the study offers a more comprehensive framework for understanding how multiple, interacting forces shape AI implementation at the country level.

This paper provides several practical implications for policymakers. First, it highlights the importance of balance in governance: while regulations and frameworks are essential to ensure trust and accountability, excessive or overlapping governance can slow implementation, leaving countries highly “ready” but unable to translate this readiness into action. Second, the findings emphasize the importance of investing in technology enablers such as infrastructure and digital skills, but also of strengthening macro-environmental conditions. Finally, the study shows that strategies must be context sensitive. Developed countries may need to avoid overregulation that hinders experimentation, while developing countries often face more fundamental challenges such as weak institutions, limited infrastructure, and shortages of expertise. Recognizing these different conditions allows policymakers to design AI ecosystems tailored to their context, balancing governance, technology, and environmental factors in ways that accelerate sustainable and effective implementation.

Future Research

Future research can further explore various factors that could increase the citizens' adoption rates of public services, and strategies that could be adopted by governments to accelerate their digital transformation initiatives in a way that meets the citizens' demand. For instance, First, future research can analyze the change in citizen adoption rates over time and identify factors impacting the positive change. Second, analyze the impact of different extrinsic motivators such as awards, points, and coupons. Third, consider enhancing the generalizability of the research by expanding it to different nations. Fourth, the sentiment analysis could be further enhanced by incorporating the demographic attributes of the users to assess variations according to different attributes such as age, education level, income and location, Fourth, expand the media frames analysis to include emerging topics such as privacy concerns Finally, future research can use primary data directly from citizens' and governments, which will help to overcome the limitations associated with secondary global indices, which might not fully capture country-specific contextual factors.

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Appendices

Appendix 1: Robustness Checks and Further Results

1. Robustness Check

We re-estimated the models by employing linear regression. Table 1 in Appendix 1 shows the results for the line regressions. The results are consistent with the logit regressions results. The impact of the explanatory variable, external reward, on e-government service adoption is both significant and positive $\beta = 0.096$ ($p < 0.01$). The moderation impact of the socio-economic conditions using the linear regression model is also similar to the logit regression results. The moderation impact of age is negative and significant $\beta = -0.040$ ($p < 0.01$) and positive and significant for the quadratic term significant $\beta = 0.001$ ($p < 0.01$). Additionally, the interaction between the low income and external rewards is significant and positive $\beta = 0.160$ ($p < 0.01$) and the interaction between the rural location and external rewards is significant and positive $\beta = 0.136$ ($p < 0.01$). The moderation impact of the digital skills and literacy using the linear regression model also produced similar results, the moderation impact of education is negative and significant $\beta = -0.029$ ($p < 0.01$). Additionally, the moderation impact of the lack of digital skills is significant and positive $\beta = 0.200$ ($p < 0.05$).

To further explore the relationship between external rewards and the adoption of e-government services, we conducted Poisson regression and negative binomial regression analyses. These methods were employed to assess the impact of external rewards, along with key moderating variables (such as socio-economic conditions and digital skills), on the number of access methods individuals used to engage with e-government services. Specifically, these regressions allow us to model the count data related to the number of

different methods adopted by users, such as mobile applications, websites, and knowledge stations, rather than focusing solely on whether individuals adopted e-government services or not.

Tables 2 and 3 in Appendix 1 present the results of these analyses. Table 2 shows the results from the Poisson regression model, while Table 3 displays the results from the negative binomial regression model. Both tables provide evidence that the impact of external rewards on e-government service adoption is significant and positive, with coefficients of $\beta = 0.170$ ($p < 0.05$) in the Poisson model and $\beta = 0.196$ ($p < 0.05$) in the negative binomial model. These results indicate that individuals who receive external rewards are likely to adopt a greater number of access methods for e-government services. This reinforces the notion that external rewards play a crucial role in encouraging broader engagement with digital government platforms.

2. Further Results

We employed logit regression to test the impact of the interaction between the external reward and the moderating variable on e-government service adoption through each of the six adoption methods separately. The detailed results are shown in tables 4 to 9 below. Table 4 shows the logit regression results for e-government services adoption using the e-government website. The first model indicates the impact of the control variables on the dependent variable. Age had a positive and significant impact on adoption $\beta = 0.081$ ($p < 0.01$) and the quadratic term of age had a negative and significant impact on adoption $\beta = -0.001$ ($p < 0.01$), the education years had a positive and significant impact on adoption $\beta = 0.141$ ($p < 0.01$). The rural location had a negative and significant impact on the adoption $\beta = -0.650$ ($p < 0.01$), the lack of IT skills had a negative and significant impact

on the adoption $\beta = -0.602$ ($p < 0.01$), the low income had a negative and significant impact on the adoption $\beta = -0.602$ ($p < 0.01$). The second model shows that external reward does not have an impact on e-government services adoption through the e-government website.

Table 5 shows the logit regression results for e-government services adoption using the Sanad Mobile application. The first model indicates the impact of the control variables on the dependent variable. Age had a positive and significant impact on adoption $\beta = 0.104$ ($p < 0.01$) and the quadratic term of age had a negative and significant impact on adoption $\beta = -0.001$ ($p < 0.01$), the education years had a positive and significant impact on adoption $\beta = 0.100$ ($p < 0.01$). The rural location had a negative and significant impact on the adoption $\beta = -0.877$ ($p < 0.01$), the lack of IT skills had a negative and significant impact on the adoption $\beta = -0.910$ ($p < 0.01$), the low income had a negative and significant impact on the adoption $\beta = -0.546$ ($p < 0.01$). The second model shows that external reward has a positive and significant impact on adoption $\beta = 0.417$ ($p < 0.01$), models 3 to 7 shows the moderation impact of the variables, only the lack of IT skills had a positive and significant impact on the relationship between the external reward and adoption through Sanad App. $\beta = 1.006$ ($p < 0.05$). Table 6 shows the logit regression results for e-government services adoption using the government entity mobile application. The first model indicates the impact of the control variables on the dependent variable. Age had a positive and significant impact on adoption $\beta = 0.098$ ($p < 0.01$) and the quadratic term of age had a negative and significant impact on adoption $\beta = -0.001$ ($p < 0.01$), the education years had a positive and significant impact on adoption $\beta = 0.136$ ($p < 0.01$). The rural location had a negative and significant impact on the adoption $\beta = -$

0.570 ($p < 0.01$), the lack of IT skills had a negative and significant impact on the adoption $\beta = -0.899$ ($p < 0.01$), the low income had a negative and significant impact on the adoption $\beta = -0.524$ ($p < 0.01$). The second model shows that external reward does not have an impact on e-government services adoption through the entity mobile application.

Table 7 shows the logit regression results for e-government services adoption using the government entity website. The first model indicates the impact of the control variables on the dependent variable. Age had a positive and significant impact on adoption $\beta = 0.103$ ($p < 0.01$) and the quadratic term of age had a negative and significant impact on adoption $\beta = -0.001$ ($p < 0.01$), the education years had a positive and significant impact on adoption $\beta = 0.125$ ($p < 0.01$). The rural location had a negative and significant impact on the adoption $\beta = -0.606$ ($p < 0.01$), the lack of IT skills had a negative and significant impact on the adoption $\beta = -0.545$ ($p < 0.01$), the low income had a negative and significant impact on the adoption $\beta = -0.393$ ($p < 0.01$). The second model shows that external reward does not have an impact on e-government service adoption through the entity's mobile application.

Table 1: Linear Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.008*** (0.001)	0.011*** (0.001)	0.029*** (0.003)	0.011*** (0.001)	0.011*** (0.001)	0.013*** (0.001)	0.011*** (0.001)
Age ²	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Gender	-0.148*** (0.009)	-0.146*** (0.009)	-0.144*** (0.009)	-0.145*** (0.009)	-0.145*** (0.009)	-0.155*** (0.009)	-0.146*** (0.009)
Education Years	-0.053*** (0.003)	-0.052*** (0.003)	-0.047*** (0.003)	-0.050*** (0.003)	-0.051*** (0.003)	-0.035*** (0.004)	-0.051*** (0.003)
Education Years ²	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Rural	-0.074*** (0.009)	-0.073*** (0.009)	-0.074*** (0.009)	-0.093*** (0.010)	-0.074*** (0.009)	-0.078*** (0.009)	-0.073*** (0.009)
Lack IT Skills	-0.135*** (0.026)	-0.133*** (0.026)	-0.129*** (0.025)	-0.132*** (0.025)	-0.133*** (0.026)	-0.134*** (0.025)	-0.152*** (0.026)
Low Income	-0.011 (0.013)	-0.011 (0.013)	-0.004 (0.013)	-0.011 (0.013)	-0.036** (0.015)	-0.005 (0.013)	-0.011 (0.013)
Personal Computer	0.098*** (0.015)	0.101*** (0.015)	0.112*** (0.015)	0.099*** (0.015)	0.099*** (0.015)	0.092*** (0.015)	0.100*** (0.015)
Laptop	0.149*** (0.015)	0.151*** (0.015)	0.161*** (0.015)	0.150*** (0.015)	0.149*** (0.015)	0.144*** (0.015)	0.151*** (0.015)
Tablet	0.007 (0.041)	0.005 (0.041)	0.004 (0.041)	0.006 (0.041)	0.002 (0.041)	0.008 (0.040)	0.004 (0.041)
Smartphone	-0.112*** (0.012)	-0.110*** (0.012)	-0.108*** (0.012)	-0.110*** (0.012)	-0.111*** (0.012)	-0.109*** (0.012)	-0.110*** (0.012)
External Reward		0.096*** (0.020)	0.899*** (0.127)	0.049** (0.022)	0.068*** (0.021)	0.299*** (0.030)	-0.100 (0.083)
External Reward#Age			-0.040***				

External Reward#Age ²			(0.005)				
			0.001***				
			(0.000)				
External Reward#Rural				0.136***			
				(0.024)			
External Reward#Low Income					0.160***		
					(0.030)		
External Reward#Education Years						-0.029***	
						(0.007)	
External Reward#Education Years ²						0.000	
						(0.000)	
External Reward#Lack IT Skills							0.200**
							(0.082)
_cons	0.680***	0.629***	0.327***	0.634***	0.637***	0.492***	0.646***
	(0.041)	(0.042)	(0.055)	(0.042)	(0.042)	(0.046)	(0.042)
N	10703	10703	10703	10703	10703	10703	10703
Log likelihood	-6944.528	-6934.040	-6893.938	-6920.527	-6923.936	-6883.688	-6932.136
R-sq.							

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Poisson Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.059*** (0.005)	0.067*** (0.006)	0.095*** (0.008)	0.068*** (0.006)	0.067*** (0.006)	0.065*** (0.006)	0.067*** (0.006)
Age ²	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Gender	-0.590*** (0.028)	-0.588*** (0.028)	-0.587*** (0.028)	-0.589*** (0.028)	-0.588*** (0.028)	-0.592*** (0.028)	-0.588*** (0.028)
Education Years	0.143*** (0.018)	0.144*** (0.018)	0.143*** (0.018)	0.144*** (0.018)	0.144*** (0.018)	0.140*** (0.022)	0.144*** (0.018)
Education Years ²	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
Rural	-0.441*** (0.032)	-0.441*** (0.032)	-0.441*** (0.032)	-0.431*** (0.033)	-0.441*** (0.032)	-0.443*** (0.032)	-0.441*** (0.032)
Lack IT Skills	-0.267*** (0.052)	-0.263*** (0.052)	-0.256*** (0.052)	-0.262*** (0.052)	-0.263*** (0.052)	-0.259*** (0.052)	-0.249*** (0.054)
Low Income	-0.363*** (0.059)	-0.361*** (0.059)	-0.346*** (0.059)	-0.360*** (0.059)	-0.357*** (0.062)	-0.360*** (0.059)	-0.361*** (0.059)
Personal Computer	0.344*** (0.035)	0.349*** (0.035)	0.356*** (0.035)	0.351*** (0.035)	0.349*** (0.035)	0.343*** (0.035)	0.350*** (0.035)
Laptop	0.397*** (0.034)	0.401*** (0.034)	0.411*** (0.034)	0.402*** (0.034)	0.401*** (0.034)	0.396*** (0.034)	0.402*** (0.034)
Tablet	0.076 (0.091)	0.074 (0.091)	0.061 (0.091)	0.072 (0.091)	0.074 (0.091)	0.073 (0.091)	0.075 (0.091)
Smartphone	-0.017 (0.037)	-0.015 (0.037)	-0.014 (0.037)	-0.014 (0.037)	-0.015 (0.037)	-0.014 (0.037)	-0.015 (0.037)
External Reward		0.170** (0.071)	-0.031 (0.850)	0.201*** (0.076)	0.173** (0.073)	0.221 (0.242)	0.300* (0.167)
External Reward#Age			-0.030				

External Reward#Age ²			(0.028)				
			0.001**				
			(0.000)				
External Reward#Rural				-0.158			
				(0.137)			
External Reward#Low Income					-0.054		
					(0.190)		
External Reward#Education Years						0.014	
						(0.039)	
External Reward#Education Years ²						-0.001	
						(0.002)	
External Reward#Lack IT Skills							-0.140
							(0.163)
_cons	-2.055***	-2.174***	-2.602***	-2.186***	-2.175***	-2.146***	-2.185***
	(0.158)	(0.167)	(0.184)	(0.167)	(0.167)	(0.185)	(0.168)
<i>N</i>	9007	9007	9007	9007	9007	9007	9007
Log likelihood	-	-	-	-	-	-	-
	11525.656	11521.760	11499.939	11520.569	11521.714	11518.860	11521.296
R-sq.	0.135	0.135	0.137	0.135	0.135	0.135	0.135

Table 3: Negative Binomial Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.063*** (0.005)	0.071*** (0.006)	0.101*** (0.009)	0.072*** (0.006)	0.071*** (0.006)	0.069*** (0.006)	0.071*** (0.006)
Age ²	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Gender	-0.652*** (0.030)	-0.650*** (0.030)	-0.647*** (0.030)	-0.650*** (0.030)	-0.650*** (0.030)	-0.654*** (0.030)	-0.650*** (0.030)
Education Years	0.117*** (0.020)	0.118*** (0.020)	0.120*** (0.020)	0.118*** (0.020)	0.118*** (0.020)	0.112*** (0.024)	0.118*** (0.020)
Education Years ²	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Rural	-0.474*** (0.033)	-0.474*** (0.033)	-0.474*** (0.033)	-0.463*** (0.034)	-0.474*** (0.033)	-0.475*** (0.033)	-0.474*** (0.033)
Lack IT Skills	-0.316*** (0.058)	-0.311*** (0.058)	-0.306*** (0.058)	-0.310*** (0.058)	-0.311*** (0.058)	-0.308*** (0.059)	-0.297*** (0.061)
Low Income	-0.361*** (0.060)	-0.358*** (0.060)	-0.344*** (0.060)	-0.358*** (0.060)	-0.354*** (0.063)	-0.358*** (0.060)	-0.358*** (0.060)
Personal Computer	0.376*** (0.039)	0.382*** (0.039)	0.393*** (0.039)	0.384*** (0.039)	0.382*** (0.039)	0.376*** (0.040)	0.382*** (0.039)
Laptop	0.437*** (0.038)	0.442*** (0.038)	0.454*** (0.038)	0.443*** (0.038)	0.442*** (0.038)	0.436*** (0.038)	0.443*** (0.038)
Tablet	0.100 (0.106)	0.098 (0.106)	0.094 (0.107)	0.097 (0.106)	0.098 (0.106)	0.099 (0.106)	0.099 (0.106)
Smartphone	-0.007 (0.038)	-0.005 (0.038)	-0.003 (0.038)	-0.004 (0.038)	-0.005 (0.038)	-0.004 (0.038)	-0.005 (0.038)
External Reward		0.196** (0.079)	-0.024 (0.840)	0.235*** (0.083)	0.200** (0.081)	0.175 (0.241)	0.318 (0.194)
External Reward#Age			-0.031 (0.029)				

External Reward#Age ²			0.001** (0.000)				
External Reward#Rural				-0.173 (0.146)			
External Reward#Low Income					-0.061 (0.198)		
External Reward#Education Years						0.029 (0.041)	
External Reward#Education Years ²						-0.002 (0.002)	
External Reward#Lack IT Skills							-0.129 (0.189)
_cons	-1.955*** (0.169)	-2.088*** (0.180)	-2.552*** (0.202)	-2.103*** (0.180)	-2.091*** (0.181)	-2.044*** (0.197)	-2.099*** (0.181)
/							
lnalpha	-0.510*** (0.050)	-0.513*** (0.050)	-0.526*** (0.050)	-0.513*** (0.050)	-0.513*** (0.050)	-0.514*** (0.050)	-0.513*** (0.050)
N	9007	9007	9007	9007	9007	9007	9007
Log likelihood	-	-	-	-	-	-	-
R-sq.	11132.550 0.081	11129.727 0.082	11116.003 0.083	11128.832 0.082	11129.687 0.082	11127.593 0.082	11129.572 0.082

Table 4: Logit Regression – E-government website

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.081*** (0.011)	0.088*** (0.013)	0.125*** (0.018)	0.089*** (0.013)	0.089*** (0.013)	0.083*** (0.013)	0.087*** (0.013)
Age ²	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Gender	-0.841*** (0.063)	-0.839*** (0.063)	-0.838*** (0.063)	-0.841*** (0.063)	-0.841*** (0.063)	-0.846*** (0.063)	-0.840*** (0.063)
Education Years	0.141*** (0.047)	0.142*** (0.047)	0.143*** (0.046)	0.142*** (0.046)	0.142*** (0.047)	0.086* (0.051)	0.139*** (0.046)
Education Years ²	0.001 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.003 (0.002)	0.001 (0.002)
Rural	-0.650*** (0.068)	-0.650*** (0.068)	-0.653*** (0.069)	-0.628*** (0.070)	-0.650*** (0.068)	-0.656*** (0.069)	-0.651*** (0.068)
Lack IT Skills	-0.602*** (0.156)	-0.598*** (0.156)	-0.595*** (0.156)	-0.596*** (0.156)	-0.597*** (0.156)	-0.581*** (0.156)	-0.519*** (0.165)
Low Income	-0.509*** (0.124)	-0.508*** (0.124)	-0.489*** (0.124)	-0.506*** (0.124)	-0.451*** (0.126)	-0.511*** (0.124)	-0.508*** (0.124)
Personal Computer	0.642*** (0.088)	0.646*** (0.089)	0.660*** (0.089)	0.649*** (0.089)	0.647*** (0.089)	0.637*** (0.089)	0.647*** (0.088)
Laptop	0.733*** (0.084)	0.736*** (0.084)	0.749*** (0.085)	0.737*** (0.084)	0.737*** (0.084)	0.724*** (0.084)	0.738*** (0.084)
Tablet	-0.044 (0.248)	-0.046 (0.249)	-0.057 (0.252)	-0.050 (0.249)	-0.045 (0.249)	-0.034 (0.249)	-0.045 (0.249)

Smartphone	0.093 (0.077)	0.095 (0.077)	0.097 (0.077)	0.097 (0.077)	0.095 (0.077)	0.097 (0.077)	0.095 (0.077)
External Reward		0.151 (0.164)	-2.075 (2.266)	0.230 (0.176)	0.207 (0.169)	-1.019 (0.641)	0.887* (0.494)
External Reward#Age			0.022 (0.071)				
External Reward#Age ²			0.000 (0.001)				
External Reward#Rural				-0.386 (0.298)			
External Reward#Low Income					-1.230* (0.730)		
External Reward#Education Years						0.251** (0.106)	
External Reward#Education Years ²						-0.012*** (0.004)	
External Reward#Lack IT Skills							-0.778 (0.487)
_cons	-4.076*** (0.378)	-4.177*** (0.398)	-4.736*** (0.440)	-4.209*** (0.399)	-4.205*** (0.399)	-3.818*** (0.416)	-4.231*** (0.401)
<i>N</i>	9070	9070	9070	9070	9070	9070	9070
Log likelihood	-3564.718	-3564.334	-3559.158	-3563.431	-3562.417	-3560.120	-3563.066
R-sq.	0.139	0.139	0.140	0.139	0.139	0.140	0.139

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Logit Regression – Sanad App

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.104*** (0.009)	0.121*** (0.011)	0.174*** (0.014)	0.123*** (0.011)	0.120*** (0.011)	0.120*** (0.011)	0.122*** (0.010)
Age ²	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Gender	-1.065*** (0.050)	-1.061*** (0.050)	-1.057*** (0.050)	-1.062*** (0.050)	-1.059*** (0.050)	-1.071*** (0.050)	-1.060*** (0.050)
Education Years	0.100*** (0.027)	0.105*** (0.027)	0.111*** (0.027)	0.105*** (0.027)	0.105*** (0.027)	0.124*** (0.031)	0.106*** (0.027)
Education Years ²	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)
Rural	-0.877*** (0.052)	-0.878*** (0.052)	-0.881*** (0.052)	-0.862*** (0.053)	-0.878*** (0.052)	-0.882*** (0.052)	-0.878*** (0.052)
Lack IT Skills	-0.910*** (0.183)	-0.898*** (0.184)	-0.902*** (0.184)	-0.896*** (0.185)	-0.899*** (0.184)	-0.903*** (0.184)	-1.019*** (0.199)
Low Income	-0.546*** (0.080)	-0.542*** (0.080)	-0.518*** (0.080)	-0.540*** (0.080)	-0.576*** (0.083)	-0.540*** (0.080)	-0.542*** (0.080)
Personal Computer	0.778*** (0.081)	0.793*** (0.081)	0.832*** (0.082)	0.795*** (0.081)	0.791*** (0.081)	0.784*** (0.081)	0.793*** (0.081)
Laptop	0.925*** (0.078)	0.935*** (0.078)	0.963*** (0.079)	0.936*** (0.078)	0.933*** (0.078)	0.927*** (0.078)	0.934*** (0.078)
Tablet	0.310 (0.212)	0.307 (0.213)	0.317 (0.216)	0.305 (0.213)	0.304 (0.212)	0.306 (0.212)	0.307 (0.213)

Smartphone	0.012 (0.057)	0.016 (0.057)	0.022 (0.058)	0.018 (0.057)	0.016 (0.057)	0.018 (0.058)	0.017 (0.057)
External Reward		0.417*** (0.137)	0.093 (1.435)	0.483*** (0.151)	0.366** (0.143)	0.916*** (0.319)	-0.562 (0.518)
External Reward#Age			-0.056 (0.049)				
External Reward#Age ²			0.001** (0.000)				
External Reward#Rural				-0.245 (0.217)			
External Reward#Low Income					0.454 (0.307)		
External Reward#Education Years						-0.068 (0.063)	
External Reward#Education Years ²						0.001 (0.003)	
External Reward#Lack IT Skills							1.006** (0.511)
_cons	-2.169*** (0.291)	-2.453*** (0.308)	-3.263*** (0.343)	-2.482*** (0.309)	-2.427*** (0.308)	-2.562*** (0.323)	-2.348*** (0.318)
<i>N</i>	9036	9036	9036	9036	9036	9036	9036
Log likelihood	-5155.517	-5150.815	-5134.620	-5150.113	-5149.728	-5148.082	-5149.033
R-sq.	0.156	0.157	0.160	0.157	0.157	0.158	0.158

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Logit Regression – Entity App

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.098*** (0.012)	0.107*** (0.014)	0.144*** (0.019)	0.108*** (0.014)	0.109*** (0.014)	0.106*** (0.015)	0.107*** (0.014)
Age ²	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Gender	-0.892*** (0.069)	-0.890*** (0.069)	-0.889*** (0.069)	-0.891*** (0.069)	-0.892*** (0.069)	-0.890*** (0.069)	-0.890*** (0.069)
Education Years	0.136*** (0.048)	0.137*** (0.048)	0.137*** (0.047)	0.137*** (0.048)	0.137*** (0.048)	0.120** (0.053)	0.135*** (0.048)
Education Years ²	0.001 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.001 (0.002)	0.001 (0.002)
Rural	-0.570*** (0.074)	-0.570*** (0.074)	-0.572*** (0.074)	-0.553*** (0.076)	-0.569*** (0.074)	-0.571*** (0.074)	-0.570*** (0.074)
Lack IT Skills	-0.899*** (0.158)	-0.893*** (0.158)	-0.891*** (0.158)	-0.892*** (0.158)	-0.893*** (0.158)	-0.889*** (0.158)	-0.828*** (0.166)
Low Income	-0.524*** (0.139)	-0.522*** (0.139)	-0.503*** (0.139)	-0.521*** (0.139)	-0.454*** (0.141)	-0.523*** (0.139)	-0.522*** (0.139)
Personal Computer	0.502*** (0.095)	0.507*** (0.096)	0.519*** (0.096)	0.510*** (0.096)	0.508*** (0.096)	0.505*** (0.096)	0.509*** (0.095)
Laptop	0.554*** (0.091)	0.559*** (0.091)	0.571*** (0.091)	0.560*** (0.091)	0.560*** (0.091)	0.556*** (0.091)	0.560*** (0.091)
Tablet	0.084 (0.240)	0.082 (0.240)	0.069 (0.241)	0.079 (0.240)	0.083 (0.240)	0.085 (0.240)	0.084 (0.240)
Smartphone	0.066	0.069	0.070	0.070	0.069	0.069	0.068

	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)
External Reward		0.207 (0.174)	-1.840 (3.341)	0.270 (0.188)	0.272 (0.179)	-0.156 (0.709)	0.809 (0.530)
External Reward#Age			0.015 (0.103)				
External Reward#Age ²			0.000 (0.001)				
External Reward#Rural				-0.297 (0.304)			
External Reward#Low Income					-1.712* (1.037)		
External Reward#Education Years						0.073 (0.117)	
External Reward#Education Years ²						-0.003 (0.005)	
External Reward#Lack IT Skills							-0.641 (0.525)
_cons	-4.263*** (0.403)	-4.408*** (0.420)	-4.973*** (0.467)	-4.433*** (0.421)	-4.442*** (0.421)	-4.298*** (0.447)	-4.452*** (0.422)
<i>N</i>	9067	9067	9067	9067	9067	9067	9067
Log likelihood	-3165.905	-3165.267	-3160.728	-3164.788	-3162.904	-3164.984	-3164.395
R-sq.	0.132	0.132	0.133	0.132	0.132	0.132	0.132

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Logit Regression – Entity Website

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.103*** (0.010)	0.108*** (0.012)	0.154*** (0.017)	0.109*** (0.013)	0.109*** (0.013)	0.102*** (0.012)	0.108*** (0.012)
Age ²	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Gender	-0.991*** (0.059)	-0.989*** (0.059)	-0.986*** (0.059)	-0.990*** (0.059)	-0.990*** (0.059)	-1.001*** (0.059)	-0.990*** (0.059)
Education Years	0.125*** (0.040)	0.126*** (0.040)	0.133*** (0.040)	0.126*** (0.040)	0.126*** (0.040)	0.082* (0.044)	0.124*** (0.040)
Education Years ²	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.003* (0.002)	0.001 (0.002)
Rural	-0.606*** (0.064)	-0.606*** (0.064)	-0.609*** (0.064)	-0.599*** (0.065)	-0.605*** (0.064)	-0.613*** (0.064)	-0.606*** (0.064)
Lack IT Skills	-0.545*** (0.159)	-0.542*** (0.159)	-0.541*** (0.160)	-0.542*** (0.159)	-0.542*** (0.159)	-0.527*** (0.159)	-0.472*** (0.168)
Low Income	-0.393*** (0.109)	-0.392*** (0.109)	-0.373*** (0.109)	-0.391*** (0.109)	-0.364*** (0.112)	-0.394*** (0.109)	-0.392*** (0.109)
Personal Computer	0.742*** (0.084)	0.745*** (0.084)	0.769*** (0.086)	0.746*** (0.085)	0.746*** (0.084)	0.731*** (0.085)	0.746*** (0.084)
Laptop	0.759*** (0.081)	0.762*** (0.081)	0.784*** (0.082)	0.762*** (0.081)	0.763*** (0.081)	0.746*** (0.081)	0.763*** (0.081)
Tablet	0.044 (0.224)	0.043 (0.224)	0.032 (0.228)	0.042 (0.224)	0.044 (0.224)	0.060 (0.223)	0.045 (0.224)
Smartphone	-0.130* (0.064)	-0.129* (0.064)	-0.125* (0.064)	-0.128* (0.065)	-0.129* (0.064)	-0.126* (0.064)	-0.129* (0.064)

	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)
External Reward		0.113 (0.159)	1.815 (1.856)	0.140 (0.171)	0.145 (0.162)	-0.610 (0.533)	0.798 (0.514)
External Reward#Age			-0.110* (0.062)				
External Reward#Age ²			0.001** (0.001)				
External Reward#Rural				-0.113 (0.268)			
External Reward#Low Income					-0.433 (0.480)		
External Reward#Education Years						0.194** (0.093)	
External Reward#Education Years ²						-0.010** (0.004)	
External Reward#Lack IT Skills							-0.717 (0.508)
_cons	-4.143*** (0.349)	-4.221*** (0.370)	-4.961*** (0.409)	-4.231*** (0.371)	-4.236*** (0.371)	-3.934*** (0.384)	-4.271*** (0.373)
<i>N</i>	9072	9072	9072	9072	9072	9072	9072
Log-likelihood	-3961.984	-3961.732	-3953.909	-3961.632	-3961.262	-3956.836	-3960.705
R-sq.	0.157	0.157	0.158	0.157	0.157	0.158	0.157

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Logit Regression – Electronic Booth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.064 (0.045)	0.067 (0.049)	0.048 (0.070)	0.063 (0.049)	0.068 (0.050)	0.080 (0.050)	0.067 (0.048)
Age ²	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Gender	-1.362*** (0.292)	-1.362*** (0.292)	-1.365*** (0.291)	-1.361*** (0.292)	-1.362*** (0.292)	-1.344*** (0.293)	-1.365*** (0.292)
Education Years	0.263 (0.184)	0.262 (0.184)	0.273 (0.190)	0.264 (0.183)	0.262 (0.184)	0.300 (0.222)	0.268 (0.185)
Education Years ²	-0.006 (0.007)	-0.006 (0.007)	-0.006 (0.007)	-0.006 (0.007)	-0.006 (0.007)	-0.008 (0.008)	-0.006 (0.007)
Rural	0.144 (0.249)	0.145 (0.249)	0.143 (0.248)	0.105 (0.255)	0.145 (0.249)	0.161 (0.252)	0.146 (0.249)
Lack IT Skills	-0.725* (0.407)	-0.724* (0.408)	-0.726* (0.409)	-0.728* (0.409)	-0.725* (0.408)	-0.769* (0.406)	-0.811* (0.414)
Low Income	-0.524 (0.605)	-0.524 (0.606)	-0.520 (0.606)	-0.524 (0.606)	-0.474 (0.607)	-0.518 (0.606)	-0.522 (0.606)
Personal Computer	0.491 (0.337)	0.493 (0.338)	0.484 (0.337)	0.477 (0.337)	0.493 (0.338)	0.518 (0.338)	0.478 (0.338)
Laptop	1.668*** (0.335)	1.670*** (0.332)	1.656*** (0.332)	1.666*** (0.332)	1.670*** (0.332)	1.689*** (0.332)	1.672*** (0.334)
Tablet	0.260 (0.796)	0.259 (0.796)	0.273 (0.796)	0.267 (0.796)	0.259 (0.796)	0.277 (0.784)	0.238 (0.799)
Smartphone	1.447***	1.447***	1.447***	1.440***	1.447***	1.441***	1.441***

	(0.332)	(0.331)	(0.333)	(0.330)	(0.332)	(0.332)	(0.330)
External Reward		0.077 (0.700)	-210.567** (86.576)	-0.185 (0.815)	0.114 (0.709)	-8.685 (6.897)	0.195 (0.687)
External Reward#Age			6.559** (2.644)				
External Reward#Age ²			-0.051** (0.020)				
External Reward#Rural				0.653 (0.934)			
External Reward#Low Income					0.000 (.)		
External Reward#Education Years						0.876 (0.803)	
External Reward#Education Years ²						-0.019 (0.023)	
External Reward#Lack IT Skills							0.000 (.)
_cons	-8.242*** (1.507)	-8.290*** (1.485)	-8.049*** (1.564)	-8.220*** (1.497)	-8.300*** (1.486)	-8.553*** (1.691)	-8.235*** (1.485)
<i>N</i>	9086	9086	9086	9086	9021	9086	9063
Log likelihood	-370.035	-370.030	-368.540	-369.813	-369.885	-368.286	-369.457
R-sq.	0.119	0.119	0.123	0.120	0.118	0.123	0.120

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Logit Regression – Knowledge Stations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.015 (0.044)	0.039 (0.061)	0.052 (0.076)	0.041 (0.062)	0.025 (0.058)	0.039 (0.064)	0.041 (0.063)
Age ²	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Gender	-0.130 (0.232)	-0.122 (0.231)	-0.124 (0.231)	-0.124 (0.231)	-0.113 (0.232)	-0.132 (0.233)	-0.122 (0.230)
Education Years	0.397* (0.223)	0.398* (0.221)	0.404* (0.229)	0.397* (0.221)	0.403* (0.222)	0.554 (0.344)	0.391* (0.222)
Education Years ²	-0.008 (0.008)	-0.009 (0.008)	-0.009 (0.008)	-0.009 (0.008)	-0.009 (0.008)	-0.014 (0.013)	-0.008 (0.008)
Rural	-0.116 (0.254)	-0.115 (0.255)	-0.115 (0.255)	-0.095 (0.263)	-0.120 (0.256)	-0.105 (0.256)	-0.118 (0.255)
Lack IT Skills	-0.844** (0.383)	-0.835** (0.382)	-0.833** (0.381)	-0.833** (0.381)	-0.831** (0.384)	-0.851** (0.378)	-0.656 (0.407)
Low Income	0.607* (0.346)	0.614* (0.347)	0.609* (0.349)	0.616* (0.347)	0.416 (0.387)	0.619* (0.348)	0.612* (0.347)
Personal Computer	0.691** (0.278)	0.707** (0.278)	0.715** (0.279)	0.711** (0.277)	0.701** (0.278)	0.700** (0.278)	0.718*** (0.278)
Laptop	0.267 (0.279)	0.280 (0.276)	0.291 (0.278)	0.282 (0.276)	0.271 (0.278)	0.282 (0.278)	0.298 (0.273)
Tablet	0.479 (0.609)	0.473 (0.607)	0.461 (0.611)	0.467 (0.607)	0.471 (0.608)	0.492 (0.604)	0.487 (0.609)
Smartphone	-0.205	-0.200	-0.202	-0.199	-0.208	-0.197	-0.192

	(0.331)	(0.331)	(0.331)	(0.331)	(0.334)	(0.331)	(0.332)
External Reward		0.592 (0.782)	5.150* (2.886)	0.684 (0.851)	0.164 (0.826)	3.295 (2.727)	1.728* (1.028)
External Reward#Age			-0.171 (0.145)				
External Reward#Age ²			0.002 (0.002)				
External Reward#Rural				-0.378 (1.093)			
External Reward#Low Income					1.883* (1.015)		
External Reward#Education Years						-0.431 (0.434)	
External Reward#Education Years ²						0.016 (0.016)	
External Reward#Lack IT Skills							-1.350 (0.959)
_cons	-7.870*** (1.779)	-8.227*** (1.873)	-8.486*** (1.709)	-8.261*** (1.895)	-8.049*** (1.883)	-9.223*** (2.425)	-8.396*** (1.906)
<i>N</i>	9086	9086	9086	9086	9086	9086	9086
Log likelihood	-419.808	-419.441	-418.929	-419.381	-417.866	-418.883	-418.576
R-sq.	0.074	0.075	0.076	0.075	0.079	0.076	0.077

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figures:

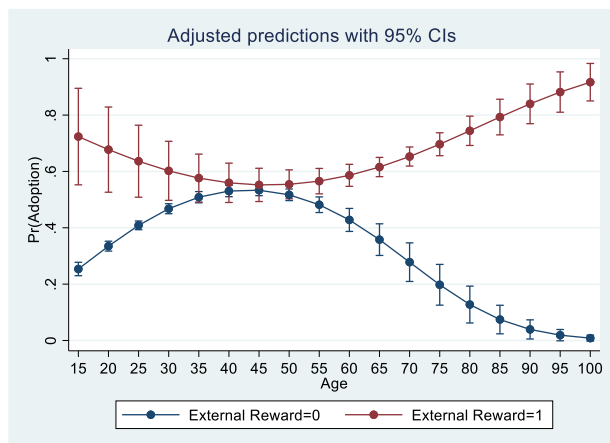


Figure 1

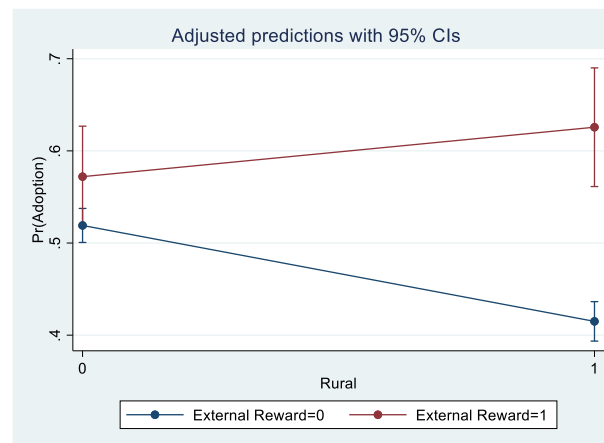


Figure 2

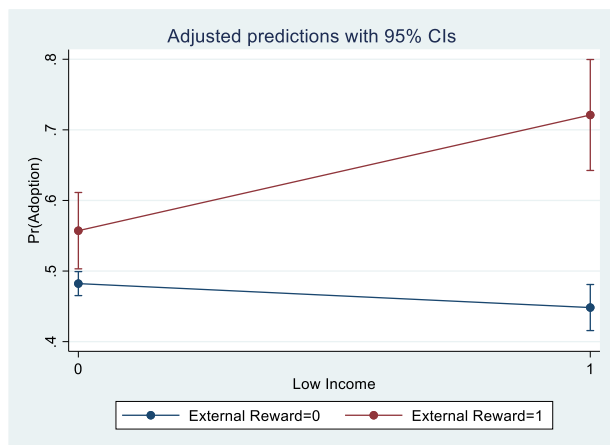


Figure 3

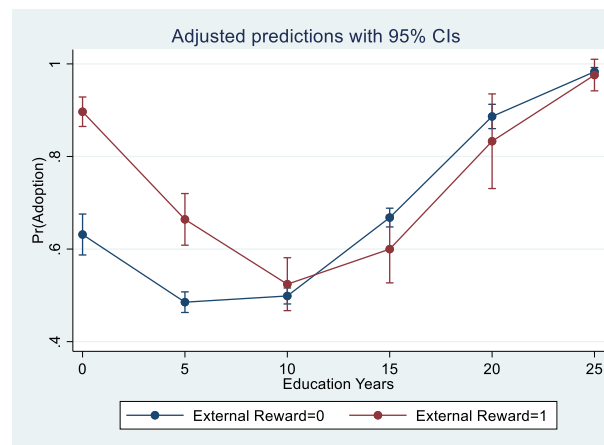


Figure 4

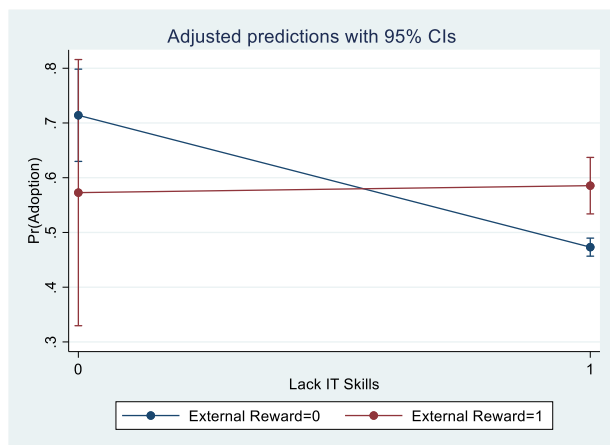


Figure 5

Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) Adoption	1.000																			
(2) Entity App	0.438	1.000																		
(3) Entity Website	0.569	0.590	1.000																	
(4) Sanad App	0.913	0.398	0.455	1.000																
(5) e-government Website	0.495	0.652	0.745	0.418	1.000															
(6) Electronic Booths	0.098	0.108	0.081	0.093	0.075	1.000														
(7) Knowledge Stations	0.102	0.125	0.103	0.083	0.114	0.165	1.000													
(8) Age	0.186	0.056	0.070	0.046	0.053	-0.001	-0.004	1.000												
(9) Age ²	0.183	0.041	0.053	0.027	0.039	-0.005	-0.006	0.979	1.000											
(10) Gender	-0.119	-0.116	-0.149	-0.192	-0.119	-0.048	-0.001	0.047	0.040	1.000										
(11) Rural	-0.104	-0.088	-0.111	-0.178	-0.106	0.007	-0.009	-0.069	-0.076	-0.008	1.000									
(12) Low Income	-0.035	-0.081	-0.089	-0.122	-0.088	-0.021	0.003	-0.047	-0.037	0.017	0.016	1.000								
(13) Education Years	0.008	0.222	0.264	0.257	0.245	0.058	0.068	-0.308	-0.342	-0.040	-0.026	-0.170	1.000							
(14) Education Years ²	0.089	0.244	0.286	0.264	0.267	0.064	0.074	-0.192	-0.225	-0.002	-0.020	-0.169	0.942	1.000						
(15) External Reward	0.163	0.007	0.010	0.002	0.009	-0.008	-0.002	0.684	0.757	0.005	-0.066	-0.001	-0.342	-0.234	1.000					
(16) Personal Computer	0.086	0.117	0.164	0.155	0.142	0.024	0.057	-0.202	-0.185	-0.034	-0.035	-0.047	0.249	0.268	-0.130	1.000				
(17) Laptop	0.139	0.159	0.204	0.211	0.191	0.070	0.046	-0.188	-0.174	0.000	-0.061	-0.105	0.320	0.353	-0.120	0.132	1.000			
(18) Tablet	0.016	0.023	0.026	0.037	0.019	0.010	0.018	-0.059	-0.052	0.001	0.000	-0.026	0.072	0.077	-0.022	0.050	0.083	1.000		
(19) Smartphone	-0.171	-0.053	-0.097	-0.093	-0.063	0.019	-0.024	-0.081	-0.096	-0.029	0.144	-0.050	0.093	0.044	-0.114	-0.190	-0.216	-0.064	1.000	
(20) Lack IT Skills	-0.096	-0.150	-0.131	-0.133	-0.134	-0.047	-0.058	0.019	0.026	-0.031	0.080	0.054	-0.155	-0.185	0.027	-0.099	-0.232	-0.072	0.064	1.000

Appendix 2: Translated questions from Jordan Technology and Internet Survey for the year 2021⁷

Category	Question	Answer Choices
Computer Equipment	In the past 12 months, did you use a computer?	1. Yes, PC 2. Yes, Laptop 3. Yes, Tablet 4. No
	What is the main reason for not using the computer?	1. Lack of knowledge 2. Unavailability of computer 3. illiterate 4. Not needed 5. I don't have time to use it 6. Using other technological alternatives (smart phones, etc.) 7. other, mention
E-Commerce	Do you use the internet for e-commerce?	1.yes 2.No 8. I don't know
E-Payments	Did you use e-banking services?	1. Yes 2. No 3. I don't have 8. I don't know
	Did you use the mobile wallet?	1. Yes 2. No 3. I don't have 8. I don't know
	Did you use internet payment methods (Google Pay, PayPal)?	1. Yes 2. No 3. I don't have 8. I don't know
E-Government	In the past 12 months did you use the websites of the government organization to get a service?	1. Yes 2. No 3. Not applicable 8. I don't know
	In the past 12 months did you use the website of the e-government	1. Yes 2. No

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https://www.modcc.gov.jo/ebv4.0/root_storage/ar/eb_list_page/%D8%A7%D9%84%D8%AA%D9%82%D8%B1%D9%8A%D8%B1_%D8%A7%D9%84%D8%AA%D8%AD%D9%84%D9%8A%D9%84%D9%8A_%D9%84%D9%86%D8%AA%D8%A7%D8%A6%D8%AC_%D9%85%D8%B3%D8%AD_%D8%A7%D8%B3%D8%AA%D8%AE%D8%AF%D8%A7%D9%85_%D9%88%D8%A7%D9%86%D8%AA%D8%B4%D8%A7%D8%B1_%D8%A7%D9%84%D8%A7%D8%AA%D8%B5%D8%A7%D9%84%D8%A7%D8%AA_%D9%88%D8%AA%D9%83%D9%86%D9%88%D9%84%D9%88%D8%AC%D9%8A%D8%A7_%D8%A7%D9%84%D9%85%D8%B9%D9%84%D9%88%D9%85%D8%A7%D8%AA_%D9%81%D9%8A_%D8%A7%D9%84%D9%85%D9%86%D8%A7%D8%B2%D9%84_2021.pdf

	www.jordan.gov.jo to get a service?	3. Not applicable 8. I don't know
	In the past 12 months did you use the mobile applications of government organizations to get a service?	1. Yes 2. No 3. Not applicable 8. I don't know
	In the past 12 months did you use SANAD mobile applications to get a service?	1. Yes 2. No 3. Not applicable 8. I don't know
	In the past 12 months did you use the electronic booths to get a service?	1. Yes 2. No 3. Not applicable 8. I don't know
	In the past 12 months did you use the Jordanian knowledge stations to get a service?	1. Yes 2. No 3. Not applicable 8. I don't know

Appendix 3: Methods

Sentiment Analysis

Sentiment Analysis is a text-based computational analysis that identifies people's opinions, attitudes, and emotions toward an entity. The sentiments may be expressed as positive, negative, or neutral (Singh & Suri, 2022). The huge volume of online data streams generates substantial noise and must be filtered in order to detect meaningful patterns and trends (Kavanaugh et al., 2012). Sentiment analysis uses natural language processing (NLP) to detect the emotions embedded in the social media content and analyze data at the gross level to provide a binary classification (positive vs. negative), neutral or ambivalent (Verma, 2022).

Sentiment analysis is a valuable tool to identify citizens' perceptions and expectations from the government (Verma, 2022; Troisi et al., 2022), sentiments extracted from the reviews can capture writers' opinion (Li et al., 2023). Online services with user-generated content made a huge amount of information available, where government officials seek to leverage this information to improve services and communication with the citizens (Kavanaugh et al., 2012)

The popularity of sentiment analysis increased after Covid-19, where scholars aim to analyze the citizens' emotions in different contexts, such as citizens' sentiment about technology before and after the pandemic (Troisi et al., 2022). Sentiment analysis systems have been applied to various kinds of texts including newspaper headlines, novels, emails, blogs, tweets, and customer reviews (Genc-Nayebi, & Abran, 2017)

The core process flow for sentiment analysis includes four steps: first, selection of the social media platform, second, data collection process, third, pre-processing of data, and finally, data analysis with polarity identification, sentiment analysis, and frequency analysis (Verma, 2022). Sentiment analysis of exchanged communication is a valuable tool to understand citizens' emotions and expectations from the government. (Verma, 2022), it can also aid in inferring the reaction towards political events, which helps in decision-making (Zahidi et al., 2021). We generated sentiment analysis of the user reviews of the m-government applications and the sentiment expressed in the press releases using SentiStrength v2.3.

Topic Modeling

Topic modeling is a major branch of natural language processing focused on inferring the generative process of unstructured text (Wheelock & Pachamano, 2022), and it's one of the most powerful techniques in text mining (Jelodar et al., 2019). The objective of topic modeling is to extract latent topics from large volumes of textual data (Walker et al., 2019), discover patterns of words and how to connect documents that share similar patterns (Alghamdi, & Alfalqi, 2015). We generated the topic modeling results for each development stage using RapidMiner Studio V10.1.

The Latent Dirichlet allocation (LDA) is one of the most frequently used methods in topic modeling (Kherwa & Bansal, 2019). LDA helps in revealing key insights hidden in the unstructured textual data, and it is one of the widely known methods for identifying patterns in texts that identify important topics (Ibrahim & Wang, 2019).

LDA is a probabilistic model of a corpus, where the documents are represented as random mixtures over latent topics, and a topic is characterized by a distribution over

words. LDA presents topics by word probabilities, therefore, the words with the highest probabilities in each topic can give valuable insights about a certain topic (Jelodar et al., 2019). LDA allows each document in a text collection to be described by a mixture of topics, with each word being attributed to a topic with different weight (Zhong & Schweidel, 2020).

Linear Regression

Regression analysis is one of the important statistical methods for analyzing data. It enables identification and characterization of the relationships among multiple variables, by employing a model that describes the relationships between the dependent variables and the explanatory variables in a simplified mathematical formula (Schneider et al., 2010).

The linear regression assumes that the relationship between the dependent and independent variables is linear, which means that a constant unit of change in the independent variable is associated with a constant unit of change in the dependent variable (Hope, 2020).

Linear regression analysis is a common used method to predict an outcome on the assumption of a linear relationship between variables, linear regression provides the best unbiased estimator for the expected change in a dependent variable,, associated with a unit change in the independent variable, and conditional on all other controls remaining constant (Wooldridge 2016). We used Stata MP 18, for regression analysis.

fsQCA

fsQCA is relatively a new and advanced approach for analyzing data, and recently, there has been a growing interest in combining fsQCA with other traditional statistical methods

in various domains such as sociology, psychology, geography, political science, life sciences, economics, and management (Geremew et al., 2024). fsQCA generates a set of explanatory variables combinations that collectively influence the outcome variable (Thu, 2024). We used fsQCA software v4.1.

This method employs a qualitative inquiry approach with quantitative exploration through configurational analysis to explain complex phenomena (Kraus et al., 2018), this method can provide a more comprehensive approach to the relationship between variables, by discovering the combinative conditions under which a negative or positive relationship can exist between two variables (Gligor & Bozkurt, 2020).

Compared to regression, the fsQCA aims to uncover different conditions that can lead to a specific outcome, while the regression determines the net effect of explanatory variables on the outcome variables, (Skarmeas et al., 2014). The fsQCA has also been used as a complementary approach to multiple regression in different domains such as customer engagement literature (Gligor & Bozkurt, 2020), strategy and business performance (Ho et al., 2016), and tourism (Zhang & Zhang, 2019).

Combining different analytical methods gives diverse perspectives on the relationships between the research variables (Thu, 2024), traditional regression analysis methods are often associated with endogeneity problems, which occurs when certain assumptions related to the data are not met, such as a normal distribution, linear relationships, and symmetry, while the fsQCA addresses endogeneity more efficiently, instead of relying on correlations, fsQCA uses Boolean algebra to analyze the relationships between the variables. This method examines the combined impact of variables on an outcome (Du et al. 2021; and Xia et al. 2024).

Appendix 4: Robustness Check

Table 1 shows the results using GLM, the first model shows the impact of the explanatory variables on the dependent variable, the technology dimension had a positive and significant effect on the AI implementation-to-readiness ratio ($\beta = 0.334$, $p < 0.01$) and the governance dimension had a negative and significant impact ($\beta = -0.231$, $p < 0.01$). The second model shows the quadratic terms of all of the four dimensions, where the quadratic term of the governance had a positive and significant effect ($\beta = 0.048$, $p < 0.01$), and the main effect for the technology was positive and significant ($\beta = 0.257$, $p < 0.01$). The third model shows the quadratic term for the technology, which was insignificant, while the main effect of the technology remains positive and significant ($\beta = 0.289$, $p < 0.01$) and governance had a negative and significant impact ($\beta = -0.221$, $p < 0.01$). The fourth model shows the quadratic term for the organization, which was insignificant, the technology had positive and significant impact ($\beta = 0.331$, $p < 0.01$), and the governance had a negative and significant impact ($\beta = -0.225$, $p < 0.01$). The fifth model shows the quadratic term of the environment which was insignificant, the technology had a positive and significant impact ($\beta = 0.333$, $p < 0.01$) and governance had a negative and significant impact ($\beta = -0.232$, $p < 0.01$). The sixth model shows the quadratic term for the governance which was positive and significant ($\beta = 0.043$, $p < 0.01$) and again finds technology positive and significant ($\beta = 0.310$, $p < 0.01$). The seventh model shows the interaction between technology and organization which was insignificant and shows the technology positive and significant ($\beta = 0.295$, $p < 0.01$) and governance negative and significant ($\beta = -0.214$, $p < 0.01$). The eight model, shows the interaction between technology and environment which was insignificant, and shows the technology positive and significant ($\beta = 0.343$, $p < 0.01$) and governance negative and

significant ($\beta = -0.237, p < 0.01$), The ninth model, shows the interaction between technology and governance which was insignificant, and shows the technology positive and significant ($\beta = 0.284, p < 0.01$) and governance negative and significant ($\beta = -0.149, p < 0.1$), model 10 shows the interaction between organization and environment which was insignificant, and shows the technology positive and significant ($\beta = 0.336, p < 0.01$) and governance negative and significant ($\beta = -0.236, p < 0.01$), model 11 shows the interaction between organization and governance which was positive and significant ($\beta = 0.058, p < 0.05$), and shows the technology positive and significant ($\beta = 0.303, p < 0.01$), and finally, model 12 shows the interaction between environment and governance which was insignificant, and shows the technology positive and significant ($\beta = 0.333, p < 0.01$), and governance negative and significant ($\beta = -0.227, p < 0.01$).

Table 2 shows, the OLS regression results, the first model shows the impact of the explanatory variables on the dependent variable, the technology dimension had a positive and significant effect on the AI implementation-to-readiness ratio ($\beta = 0.103, p < 0.01$) and the governance dimension had a negative and significant impact ($\beta = -0.073, p < 0.05$). The second model shows the quadratic terms of all of the four dimensions, where the quadratic terms of the technology and governance had a positive and significant effect ($\beta = 0.011, p < 0.01$) and ($\beta = 0.018, p < 0.01$) respectively, and the main effect for the technology was positive and significant ($\beta = 0.045, p < 0.05$). The third model shows the quadratic term for the technology, which was positive and significant ($\beta = 0.010, p < 0.01$), the main effect of the technology remains positive and significant ($\beta = 0.060, p < 0.01$) and governance had a negative and significant impact ($\beta = -0.066, p < 0.05$). The fourth model shows the quadratic term for the organization, which was insignificant, the

technology had positive and significant impact ($\beta = 0.101, p < 0.01$), and the governance had a negative and significant impact ($\beta = -0.071, p < 0.05$). The fifth model shows the quadratic term of the environment which was insignificant, the technology had a positive and significant impact ($\beta = 0.102, p < 0.01$) and governance had a negative and significant impact ($\beta = -0.075, p < 0.05$). The sixth model shows the quadratic term for the governance which was positive and significant ($\beta = 0.016, p < 0.01$) and again finds technology positive and significant ($\beta = 0.095, p < 0.01$). The seventh model shows the interaction between technology and organization which was insignificant and shows the technology positive and significant ($\beta = 0.075, p < 0.01$) and governance negative and significant ($\beta = -0.065, p < 0.05$). The eighth model, shows the interaction between technology and environment which was insignificant, and shows the technology positive and significant ($\beta = 0.106, p < 0.01$) and governance negative and significant ($\beta = -0.075, p < 0.05$). The ninth model, shows the interaction between technology and governance which was insignificant, and shows the technology positive and significant ($\beta = 0.080, p < 0.01$) and governance negative and significant ($\beta = -0.045, p < 0.1$), model 10 shows the interaction between organization and environment which was insignificant, and shows the technology positive and significant ($\beta = 0.103, p < 0.01$) and governance negative and significant ($\beta = -0.075, p < 0.05$), model 11 shows the interaction between organization and governance which was positive and significant ($\beta = 0.015, p < 0.5$), and shows the technology positive and significant ($\beta = 0.095, p < 0.01$) and governance negative and significant ($\beta = -0.045, p < 0.05$), and finally, model 12 shows the interaction between environment and governance which was insignificant, and shows the

technology positive and significant ($\beta = 0.104$, $p < 0.01$), and governance negative and significant ($\beta = -0.079$, $p < 0.05$).

Table 2: Linear Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
tech	0.103*** (0.014)	0.045** (0.017)	0.060*** (0.016)	0.101*** (0.014)	0.102*** (0.014)	0.095*** (0.016)	0.075*** (0.021)	0.106*** (0.015)	0.080*** (0.028)	0.103*** (0.014)	0.095*** (0.016)	0.104*** (0.014)
org	-0.014 (0.016)	-0.011 (0.012)	-0.008 (0.015)	-0.014 (0.016)	-0.012 (0.016)	-0.020 (0.014)	-0.007 (0.015)	-0.013 (0.016)	-0.016 (0.015)	-0.013 (0.016)	-0.017 (0.015)	-0.012 (0.016)
env	0.019 (0.017)	0.001 (0.010)	0.022 (0.016)	0.018 (0.017)	0.017 (0.016)	0.002 (0.011)	0.018 (0.017)	0.018 (0.017)	0.014 (0.014)	0.019 (0.017)	0.011 (0.014)	0.020 (0.017)
gov	-0.073** (0.030)	0.003 (0.016)	-0.066** (0.030)	-0.071** (0.030)	-0.075** (0.030)	-0.011 (0.016)	-0.065** (0.029)	-0.075** (0.030)	-0.045* (0.025)	-0.075** (0.031)	-0.045** (0.021)	-0.079** (0.034)
tech # tech		0.011*** (0.002)	0.010*** (0.002)									
org # org		0.001 (0.007)		0.003 (0.007)								
env # env		-0.005 (0.004)			-0.003 (0.004)							
gov # gov		0.018*** (0.005)				0.016*** (0.005)						
tech # org							0.017 (0.010)					
tech # env								-0.005 (0.006)				
tech # gov									0.023 (0.022)			
org # env										-0.003 (0.005)		
org # gov											0.015* (0.009)	
env # gov												-0.003 (0.006)
Constant	0.242*** (0.012)	0.196*** (0.017)	0.224*** (0.012)	0.236*** (0.017)	0.252*** (0.019)	0.205*** (0.014)	0.221*** (0.015)	0.247*** (0.013)	0.218*** (0.022)	0.248*** (0.017)	0.217*** (0.013)	0.248*** (0.017)

Observations	77	77	77	77	77	77	77	77	77	77	77	77
R-sq.	0.593	0.740	0.631	0.589	0.591	0.683	0.609	0.590	0.612	0.589	0.619	0.590

