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Factors Influencing User Perception and Adoption of E-Government Services

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Abstract: The objective of this study is to investigate and determine factors influencing user perception
and acceptance of electronic government services in the context of technological advancements. The
research focuses on classifying the main features of e-administrative systems with an emphasis on
user satisfaction by integrating both traditional and modern data analysis techniques. Structural
Equation Modelling (SEM), machine learning (ML) techniques, and multi-criteria decision-making
(MCDM) methods have been applied to survey data to uncover the interdependencies between
variables from the perspective of online users. The developed models discover and explain the
underlying relationships in user attitudes towards e-government services. As the perception of
customer satisfaction is subjective and dynamic, stakeholders should conduct regular measurements
and data analysis to ensure continuous improvement of e-public services.

Keywords: electronic public services; electronic government services; technology adoption; customer
satisfaction; behaviour intention; structural equation modelling; PLS-SEM; machine learning

1. Introduction

Electronic administrative processes streamline traditional operations, reducing costs
associated with outdated manual practices and contributing to the development of a more
efficient, transparent, and customer-centric administrative ecosystem (Doran et al. 2023).
Additionally, digital government platforms enhance connectivity via interactions over
distance through cost-effective communication systems. Digitalization in the public sector
not only improves the quality and accessibility of public services, it reshapes citizen–
government, businesses–government, and government–government relationships. More-
over, this transformation in public organizations supports the transition to cleaner energy
sources by optimizing resource usage and minimizing the need for physical inputs (Firman-
dayu and Elfaki 2023; Gomez-Trujillo and Gonzalez-Perez 2021; Hochstetter et al. 2023). The
digital evolution of public administration further facilitates the development of inclusive
institutions and positively influences the overall progress of society (Tokovska et al. 2023).
Electronic government (e-government) refers to the use of information and communication
technologies (ICT) in delivering public services. E-government instruments, including
digital platforms, IT systems, and software apps, ensure dynamic interactions remotely
even in times of crisis, as demonstrated during the COVID-19 pandemic (Hodzic et al. 2021).
Furthermore, e-government tools have the potential to offer services for vulnerable so-
cial groups, such as individuals living in poverty, older adults, people with disabilities,
immigrants, and youth by addressing their specific needs (Seljan et al. 2020).

At the global level, international organizations such as United Nations (UN), Organization for Economic Co-operation and Development (OECD), and World Bank (WB) collaborate with their member countries to facilitate the spread of e-government technologies and practices. These cooperative efforts aim to enhance openness and citizen engagement in public administration activities. For example, the UN Sustainable Development Goals (SDGs), as outlined in their 2030 Agenda (UN General Assembly 2015), closely align with the concept of e-government, emphasizing connectivity and open data availability as fundamental to a more sustainable global community (Othman et al. 2020). As a result, an increasing number of countries are prioritizing the digitization of public services. For example, in the European Union (EU), the Digital Decade programme (2022) seeks to achieve 100% online provision of "key public services" by 2030, while the goal of the Interoperable Europe Act (2022) is to boost cross-border interoperability and co-operation in the public sector. In Denmark, India, the Netherlands, and other countries, electronic public services are even mandatory for public administration (Tangi et al. 2021).

Electronic public services (e-public services, electronic administrative services, e-administrative services) encompass a wide range of activities at both central and territorial levels of government. These services include digital document submission, electronic tax filing and payment, online applications for licenses and permits, and online communication with organizational structures and entities. Their prevalence can be significantly increased, driven by technological innovations and the demand for efficient and convenient government interactions (Torres et al. 2005).

The COVID-19 pandemic and subsequent social distancing measures accelerated the dissemination of e-government services. With restrictions on in-person contacts, individuals, and businesses turned to digital channels to fulfil their administrative needs remotely. This transition has led to elevated utilization of electronic platforms for various government-related transactions even among customers who previously had limited experience or engagement with electronic public services (Chatzopoulou et al. 2021). Unfortunately, as the health situation normalizes, there has been some decrease in requests for e-administrative services. For example, in Bulgaria, during the COVID-19 health crisis, the number of provided e-administrative services increased by 130% in 2021 compared to the previous year, while in the following year (2022) it decreased by 18% (Council of Ministers 2020; Council of Ministers 2021; Council of Ministers 2022).

According to UN Electronic Government Evaluation Index (EGDI) reports, Europe has consistently held the highest average EGDI among the continents since the initiation of UN e-Government Survey in 2003. Furthermore, the development of e-government across Europe is notably more uniform compared to other continents (UN DESA 2022). The majority of surveyed European countries fall within the highest EGDI group, with eight of them ranking among the global leaders in e-government development. However, as per the EU e-Government Benchmark report (Capgemini et al. 2023), there are significant variations among European countries in key indicators such as transparency and cross-border services. Globally these differences are even more pronounced, with African countries facing the greatest lag in e-government development.

Moreover, the deployment of new e-administrative services often entails a variety of challenges extending beyond software implementation issues, such as integration, user awareness, and training needs. These issues have a negative impact on perception of e-government services. However, there is no unified framework or methodology for assessment of e-public services adoption. Examining factors influencing these attitudes and predicting their impact on the utilization of electronic public services poses a complex challenge for the following three primary reasons:

1. Recent advancements in ICT technologies, including Artificial Intelligence (AI), blockchain, and the Internet of Things (IoT) can enhance the methods and channels of e-government (Ivić et al. 2022).
2. The dynamics, uncertainty, and complexity of the economic landscape influence users' requirements, preferences, and habits. As technologies evolve, expectations

and demands of users for the channels delivering e-public services are increasingly shifting online (Solvak et al. 2019).

3. The existing methods for customer satisfaction research can be expanded through the incorporation of machine learning (ML) (AlHadid et al. 2022), fuzzy logic, big data, and other intelligent techniques or their combinations.

This enrichment requires the exploration of new dependencies in understanding user satisfaction and preferences towards e-administrative services.

The objective of this study is to examine the factors that influence user perception and intention to use e-public services. By establishing a comprehensive understanding of these factors, we aim to develop a theoretical framework and empirical models that can guide government agencies in designing and implementing effective e-administrative systems. Additionally, we investigate the impact of demographic and socioeconomic factors, such as gender, age, education level, residence area, and monthly income, on user acceptance and adoption of e-administrative services.

The main tasks of this research are as follows:

-   Propose a methodological framework that facilitates the systematic analysis of customer data and can reveal hidden relationships between factors influencing the adoption of new information technologies (IT) in the public sector;
-   Collect and systemize a customer dataset about their experiences and preferences regarding online public services (gender, age, residential area, monthly income, attitudes and opinions);
-   Create and validate a Structural Equation Model (SEM) based on factors from the literature review and assess their influence on customer attitude toward e-administrative services;
-   Identify the key factors affecting customer use and intention to use e-administrative services according to the obtained model;
-   Create and evaluate alternative ML and MCDA models for prediction of user perception and adoption of e-administrative services.

To explore customer adoption of e-government services, we divide satisfaction factors into seven main groups and employ the corresponding mathematical models for prediction. The obtained factors' weights can be integrated into multi-criteria assessment systems for evaluation of e-administrative services. The main contribution of this paper is the development of a new complex methodology incorporating structural equation and ML models with MCDM for evaluation, comparison, and prediction of customer attitudes towards e-public services.

The remainder of this paper is organised as follows: Section 2 provides an overview of e-government services and the indicators for their assessment; Section 3 reviews relevant literature on user perception and acceptance of e-public services; Section 4 outlines the research objectives and methodology; Section 5 presents the results obtained from the analysis of the collected dataset; finally, in Section 6 we discuss the implications of the study, highlight its contributions, and provide future research directions in the field of e-administrative services.

2. State of the Art Review of Digital Administrative Services

Digital public services revolutionize the way citizens and businesses interact with public administration, providing efficient ICT instruments for various transactions. These innovative services enable their users to conveniently perform everyday tasks such as document submissions, fee payments, and application processing through digital interactions. Simultaneously, they empower government agencies by transforming service delivery methods, offering added value and enhanced user experience through geographical boundaries. Additionally, these advancements foster improvements in administration-to-administration relationships, offering greater collaboration and efficiency in intergovernmental interactions.

However, a significant challenge arises, as individuals may not be fully acquainted with the capabilities of these cutting-edge administrative applications. This lack of knowledge often results in a discrepancy between the potential benefits of electronic administrative services and the needs of the citizens they serve. In this context, we explore the distinctive features of e-administrative services, emphasizing their transformative potential.

2.1. Key Features and Taxonomy of Electronic Public Services

Digital public services enclose a wide range of online services provided by governmental bodies to citizens, businesses, and other stakeholders. Recently, emerging ICT such as AI, blockchain, and IoT (Internet of Things) have reshaped the landscape of delivering such public services (Ivić et al. 2022).

Artificial Intelligence plays a significant role in automating routine administrative tasks, improving decision-making processes, and enhancing overall efficiency. AI algorithms analyse vast datasets to derive insights, enabling governments to make data-driven policy decisions and streamline service delivery. Chatbots powered by AI methods provide citizens with instant support, enhancing accessibility and responsiveness in public services (Al-Mushayt 2019).

Blockchain technology, known for its decentralized and secure nature, has brought transparency and trust to public service transactions. It ensures the integrity and immutability of records, reducing fraud and corruption risks. In areas such as identity verification and document authentication, blockchain enhances security and minimizes the risk of data manipulation. This technology is particularly valuable in creating accountable and transparent systems for public records, such as land registries and financial transactions, fostering greater trust between the government and its stakeholders (Lykidis et al. 2021).

The Internet of Things is another transformative technology that contributes to the delivery of public services. IoT devices ranging from smart sensors to connected infrastructure enable real-time monitoring and data collection. In public safety, for instance, IoT devices can enhance emergency response systems by providing accurate and timely information. Smart city initiatives leverage IoT to optimize resource management, improve transportation, and refine environmental monitoring (Bansal et al. 2022).

Integrating innovative technologies such as AI, blockchain, and IoT in delivering public services creates a technological synergy that improves efficiency while fostering more citizen-centric, secure, and responsive governance.

E-public services are also important in attracting foreign investments by establishing an accessible and transparent business environment. Countries with well-developed digital platforms for public services create a positive business climate, offering streamlined processes for regulatory compliance, licensing, and other administrative procedures. Consequently, e-public service infrastructure not only enhances the overall attractiveness of a country for foreign investments but reflects its commitment to modernization and effective governance (Al-Sadiq 2021).

Given the increasing dependence on digital business-to-consumer interactions in various aspects of everyday life, citizens expect the public sector to meet elevated standards similar to those set by business software. As technologies evolve, citizens expect e-government to provide intuitive interfaces, timely services, and a user-centric approach, aligning with the benchmarks established by successful online business applications (Holzer et al. 2019). For instance, the integrated services of the Chinese super-application WeChat, including utility payments and notifications, can be personalized to some extent based on user preferences and location (Pan 2020).

Starting in the 1990s, numerous public administration entities have implemented technological innovations by offering online alternatives to traditional service delivery methods. Electronic public services can be categorized in various ways by different criteria.

Service model: E-public services can be split by their recipients (users) and classified into three main categories: government-to-citizen (G2C), government-to-business (G2B), and government-to-government (G2G).

Service type: This criterion categorizes online public services based on their primary function, distinguishing between core government functions, citizen-centric services, and those catering to businesses and industries.

Government level: According to their administrative level, public services can be divided into three groups—central, regional, or local government offerings.

Interactivity level: Differentiates between informational, transactional, and interactive services, reflecting the extent of user engagement and functionality.

Delivery channel: E-public services can be classified according to the medium through which they are accessed—online platforms, systems, or mobile applications.

Service maturity: According to the stage model (Layne and Lee 2001), different stages represent the evolutionary progression in the implementation of electronic public services. A common stage model for e-government includes the following stages: emerging, enhanced, transactional, integrated, networked, and ubiquitous services (Lemke et al. 2020).

The widespread use of digital public services by citizens, businesses, and public administration relies on many factors, including the presence of suitable electronic infrastructure, internet availability, and the proficiency to design, implement, manage, and utilize e-government systems.

2.2. Assessing Electronic Public Services

When evaluating electronic government development, a range of assessment tools can be employed to evaluate the quality, security, and overall effectiveness of public services. These can be categorized in five main areas: (1) indices; (2) standard specifications; (3) frameworks; (4) theoretical models; and (5) metrics (Table 1). These benchmarks can complement each other in enhancing the understanding and improvement of the adoption and maturity of e-government initiatives.

Among the most widely used indices for e-government evaluation are the following:

EGDI: Published by the UN, EGDI is a composite index that measures the state of e-government development in countries based on three dimensions: online services, telecommunications infrastructure, and human capital. It ranks countries according to their e-government readiness (Hernández et al. 2024).

e-Government Benchmark: This benchmark of the European Commission assesses the digital maturity of European countries in providing online public services. It evaluates different dimensions, such as online services, online cross-border services, electronic IDentification (eID), e-documents, and pre-filled forms (Majo 2023).

Digital Government Index: The OECD defines a set of indicators to assess the maturity of digital government across its member countries. It covers aspects such as digital-by-design, data-driven public sector, government as a platform, open by default, user-driven, and proactiveness (Ubaldi and Okubo 2020).

GovTech Maturity Index: WB's index assesses the readiness of countries to participate in the digital economy. It considers factors such as the regulatory environment, technology infrastructure, and digital literacy (Dener et al. 2021).

These indices vary in their methodologies, focus areas, and the dimensions that they consider. Governments, policymakers, and researchers often use a combination of these indices to gain a comprehensive understanding of the state of e-government development globally and regionally.

Table 1. Comparison of the most widely used measurement tools for evaluating digital government services.

Assessment Tool	Measurement Goal(s)	Appraisal Dimensions	Evaluation Scope
EGDI (UN DESA 2022)	E-government development	EGDI evaluates online services, telecommunication infrastructure, human capital	Global and regional
e-Government Benchmark (EC 2023)	E-government development	The index consists of assessments of online services, online cross-border services, eID, e-documents, pre-filled forms	European
Digital Government Index (Ubaldi and Okubo 2020)	E-government development	This index comprises six e-government measures: digital-by-design, data-driven, platform-based, open, user-driven, and proactive	Global and regional
GovTech Maturity Index (Dener et al. 2021)	E-government maturity	GTMI includes four components: core government systems, public service delivery, digital citizen engagement, and GovTech enablers	Global and regional
ISO 20000 (ISO/IEC 20000-1:2018 2018)	Performance, Quality Management	Standard for IT service management, focusing on efficiency and performance	Organizational
ISO 27001 (ISO/IEC 27001:2022 2022)	Security	Standard for information security management systems, ensuring confidentiality, integrity, and availability of information	Organizational
EN 301549 (EN 301549:2018 2018)	Accessibility	This standard contains detailed requirements for websites, web-delivered documents, and mobile applications	European organizational
CAF (Prorok 2020)	Organizational Performance Assessment	The framework has nine criteria: leadership, personnel, partnerships, budget, knowledge, IT, processes, citizens and customers, social responsibility, and key performance	European organizational
SERVQUAL (Parasuraman et al. 1991)	Service Quality	This framework assesses service quality based on five factors: tangibles, reliability, responsiveness, assurance, and empathy map	Organizational
TAM (Davis 1989)	User Acceptance	Model evaluating user acceptance of technology, focusing on factors influencing users' willingness to adopt and use e-services	User-centric
UTAUT (Venkatesh et al. 2003)	User Behaviour	Model integrating various factors to predict user acceptance and behaviour toward e-public services	User-centric
UX Evaluation *	Usability, Satisfaction	Metric assessing overall user experience, encompassing usability, accessibility, and satisfaction with e-administrative services	User-centric
Digital Accessibility Evaluation *	Accessibility	Metric evaluating the accessibility of e-administrative services to ensure usability for individuals with disabilities	User-centric
Efficiency and Performance Metrics *	Performance Metrics	Metrics assessing the efficiency and performance of e-administrative services, including response time, throughput, server uptime, and resource utilization	User-centric
Citizen-Centric Evaluation *	User Satisfaction, Expectations	Metric evaluating the extent to which e-administrative services are citizen-centric and meet user needs and expectations	User-centric
Digital Inclusion Assessment *	Inclusiveness	Metric evaluating the inclusiveness of e-administrative services, ensuring accessibility to diverse user groups based on factors such as language diversity and outreach efforts	User-centric

Note: * denotes that the concept continually evolves, integrating diverse guidelines and methodologies developed by various organizations and expert groups.

The ISO/IEC standards contribute to the assessment of e-government development by offering common guidelines and measures, facilitating consistency, transparency and

interoperability across different systems for public services. They help governments to align their digital strategies with international best practices in a more efficient e-government structure. The ISO/IEC 20000 standard (ISO/IEC 20000-1:2018 2018) outlines guidelines for service management, including the planning, delivery, and improvement of IT services. Therefore, this standard can be applied to assess the quality of electronic administrative services (Sarwar et al. 2023). The ISO/IEC 27001 standard (ISO/IEC 27001:2022 2022) focuses on information security management systems and is applicable for evaluating the security aspects of electronic administrative services, ensuring the confidentiality, integrity, and availability of information. Although originally designed for quality management in general, ISO/IES 9001 can be applied to assess the quality of IT services, including electronic administrative services. It emphasizes customer satisfaction and continuous improvement. EN 301549 (EN 301549:2018 2018) is a European standard providing accessibility requirements for ICT products and services, ensuring that electronic administrative services are accessible to all users, including those with disabilities.

While ISO/IEC 20000 guides IT service management, ISO/IEC 27001 focuses on information security, ISO/IES 9001 emphasizes quality, and EN 301549 sets European accessibility requirements, these standards collectively provide a comprehensive framework to assess and enhance electronic administrative services.

A diverse range of frameworks serves to provide suitable tools for benchmarking e-public services, offering structured rules to optimize IT service management and improve the overall efficiency of digital service delivery. Information Technology Infrastructure Library (ITIL) is a set of practices for IT service management. It offers a framework for delivering high quality IT services, aligning them with the needs of the business. ITIL can enhance the management of electronic administrative services (Batmetan et al. 2022). In recent years, the Common Assessment Framework (CAF) (Prorok 2020) has been prioritized as a quality management system in the administrations of EU member states. It serves as a common framework for evaluating the performance of public sector organizations. Another instrument for e-public services assessment is the European Foundation for Quality Management (EFQM). EFQM is a framework for organizational management and quality improvement known as the EFQM Excellence Model. It is a holistic approach to assessing and improving organizational performance, focusing on leadership, strategy, people, partnerships, resources, processes, products/services, customer results, people results, society results, and key performance results (Rahmati and Jalilvand 2023). The Open Data Readiness Assessment evaluates the readiness of e-administrative services to publish and use open data. This framework provides a structured approach for assessing open data readiness (Kawashita et al. 2020).

In the assessment of e-public services, various theoretical models encompass aspects such as quality, maturity, user acceptance, and broader technology adoption in the public sector. SERVQUAL compares expectations with perceptions on different service quality aspects. Later, this model was identified with five dimensions of service quality: Tangibles, Reliability, Responsiveness, Assurance, and Empathy (Parasuraman et al. 1991). Maturity models, such as the Capability Maturity Model Integration (CMMI), can help organizations to assess and improve their processes, capabilities, and overall maturity in delivering services or solutions. They offer a systematic approach to organizations in moving from lower maturity levels to higher ones while incorporating best practices and continuous improvement. Maturity models are often applied at the organizational level to evaluate and enhance the maturity of e-governance processes, service delivery, and overall capabilities (Kawashita et al. 2020; Hujran et al. 2023). The Technology Acceptance Model (TAM) (Davis 1989) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Stefanovic et al. 2021) are user-centric models that focus on understanding and predicting user acceptance and adoption of technology, including e-government services. TAM emphasizes Perceived Ease of Use and Perceived Usefulness, while UTAUT incorporates additional factors such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions (Pedrosa et al. 2020; Zeebaree et al. 2022).

The abovementioned models for e-public service evaluation contribute distinct insights: SERVQUAL emphasizes service quality, maturity models assess evolutionary stages, TAM focuses on user acceptance, and UTAUT provides a holistic understanding of user behaviour.

Metrics for e-public services cover various aspects of user experience evaluation, ensuring usability, accessibility, and satisfaction; digital accessibility evaluation for individuals with disabilities; efficiency and performance metrics measuring response time, throughput, server uptime, and resource utilization; citizen-centric evaluation gauging user satisfaction and expectations; and digital inclusion assessment considering language diversity, accessibility features, and outreach efforts (Holzer et al. 2019).

Depending on their main features, the most widely used measurement tools for evaluating digital government services, as outlined in Table 1, can be classified based on several criteria such as assessment type, focus, methodology and application scope.

Type of Assessment: Standards such as ISO/IEC 20000 and frameworks such as CAF define structured guidelines for quality management and performance assessment, while models such as SERVQUAL and metrics such as User Experience (UX) Evaluation cover diverse aspects of gauging electronic public service.

Focus of Assessment: User-centric approaches are addressed by models such as TAM and UTAUT and metrics such as UX Evaluation and Citizen-Centric Evaluation, standards such as ISO/IEC 27001 emphasize security, and EN 301549 and the Digital Accessibility Evaluation focus on accessibility.

Methodology: Quantitative methodologies are employed in standards such as ISO/IEC 20000 and metrics such as Efficiency and Performance, Digital Accessibility Evaluation, and Digital Inclusion Assessment, while qualitative methods are applied in frameworks such as CAF and models such as SERVQUAL and UX Evaluation. Qualitative methods involve approaches such as user surveys, focus groups, in-depth interviews, and usability studies of user perceptions and overall experiences with electronic services.

Scope: Global standards such as ISO/IEC 20000 and ISO/IEC 27001 have a worldwide focus, European standards such as EN 301549 cater to a regional context, organizational assessments are addressed by frameworks such as CAF and models such as SERVQUAL, and user-centric evaluations are covered by models such as TAM and UTAUT and metrics such as UX Evaluation and Citizen-Centric Evaluation.

The multitude of measurement tools for the assessment of e-public services provides a multifaceted approach, from user experience and efficiency to security and accessibility, contributing to continuous improvement and informed decision-making in digital governance. When evaluating electronic administrative services, organizations often combine relevant measurement tools based on their specific goals, regulatory requirements, and the nature of the services provided.

2.3. Challenges in Evaluating Electronic Public Services

When assessing electronic public services through different frameworks, models, and indices, several challenges may arise. First, different frameworks and models employ varied attributes, making it difficult to compare and standardize evaluations across indices. Second, the rapid evolution of technology requires constant updates. For example, UTAUT continues to progress and be enriched. Lastly, contextual variations are an issue, as the effectiveness of evaluation frameworks may vary based on the goals and characteristics of each government or region.

To overcome these obstacles, continuous refinement and adaptation of evaluation measures are important to ensure alignment with the changing landscape of electronic public services. Considering the problem of selecting the optimal approach, we propose a combination of assessment methods for e-public services to ensure comprehensive and reliable estimates. The TAM and UTAUT models are among the most widely employed for understanding and predicting customer satisfaction in technology adoption. Their simplicity and clarity make them accessible and applicable across diverse technological

contexts. Their empirical validation in numerous studies further supports their credibility and predictive power. Additionally, the ability of TAM and UTAUT to integrate relevant factors and evolve with emerging trends contributes to their long-term popularity in both research and practice.

The next section presents a review of recent studies on customer perceptions and attitudes towards e-public services using models based on TAM and UTAUT extensions.

3. Related Work

3.1. Customer Satisfaction with Digital Public Services and Its Measurement

Over the past two decades, users' attitude toward e-government services has attracted the attention of scholars and practitioners of service delivery. Within the dynamic digital service environment, public satisfaction becomes a pivotal element influencing the spread of e-government initiatives. Broadly speaking, customer satisfaction with e-services gauges the extent to which these services fulfil or surpass citizen expectations (Rita et al. 2019). The overall user experience determines whether individuals will continue to use a specific e-government service or revert to traditional offline alternatives. Providers of e-government systems must comprehend the needs and preferences of the public in order to ensure the success of digital services.

To determine the citizen satisfaction with online government services in Greece, Papadomichelaki and Mentzas (Papadomichelaki and Mentzas 2012) examined the relationship between e-government quality from six main input dimensions—Ease of Use, Trust, Functionality of the Interaction Environment, Reliability, Content and Appearance of Information, and Citizen Support and Customer Attitude towards e-public services. Their study found that Efficiency, Reliability, Citizen Support, and Trust have positive impacts, while Ease of Use and Content and Appearance of Information do not have significant effects on service quality assessment.

Xie et al. integrated Trust and Risk into TAM and Theory of Planned Behaviour (TPB) in the Chinese e-government context (Xie et al. 2017). Their proposed conceptual model incorporated four constructs—Perceived Usefulness, Perceived Ease of Use, Perceived Risk, and Trust towards e-Government. The authors employed SEM to test their model with survey data. Their study discovered that all four constructs had a significant impact on consumer attitudes towards e-public services.

Kurfali et al. studied the underlying factors that play role in citizens' decisions to use e-government services by conducting an empirical study in Turkey (Kurfali et al. 2017). The authors developed a conceptual model that enriches UTAUT by introducing Trust of Internet and Trust of Government factors to the traditional Performance Expectancy, Effort Expectancy, Social influence, and Facilitating Conditions. They tested the model using SEM analysis with survey data. Their analysis indicated that Performance Expectancy, Social Influence, Facilitating Conditions, and Trust had a significant positive influence on consumer attitudes towards the adoption of digital public services.

Lallmahomed et al. proposed an extended theoretical framework comprising extended UTAUT and e-Government Adoption Model (GAM) features to examine the factors that affect the resistance to change and behaviour intention around use of e-public services by citizens in small island developing states (Lallmahomed et al. 2017). The UTAUT part of their conceptual model included five key constructs, consisting of four inputs (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Perceived Price Value) and one output construct (Behavioural Intention). The obtained results showed that three input UTAUT constructs had statistically significant impacts on the output indicator: Performance Expectancy, Facilitating Conditions, and Perceived Price Value.

Mensah et al. proposed and validated an extension of the Unified Model of Electronic Government Adoption (UMEGA) (Mensah et al. 2020). A conceptual model was defined consisting of 50 input variables categorized into seven input constructs (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, Perceived Service Quality, and Trust in Government) and three output constructs (Attitude,

Behaviour Intention, and Intention to Recommend). Their analysis of the obtained results confirmed the research hypothesis that the Attitude towards e-public services directly depends on the Perceived Risk from the given independent constructs.

Camilleri examined the important factors affecting Intention to Use and Actual Usage of e-public services in Scotland (Camilleri 2020). This research showed that Perceived Usefulness and Perceived Ease of Use have the maximal impact on citizen intention to engage with online government technologies. Additionally, this research found that there were significant mediating effects from Age, Gender, and User Experience related to Intention to Use and Actual Usage of e-public services.

ElKheshin and Saleeb studied the effects of TAM model attributes in combination with several social, political, and design variables on Attitude and Intention to adopt e-public services in Egyptian e-government (ElKheshin and Saleeb 2020). The results of this study indicated that both main constructs (Perceived Usefulness and Perceived Ease of Use) had positive and significant effects on digital services adoption, with Perceived Usefulness having a higher effect.

AlHadid et al. explored seven influencing factors (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, Trust, and Service Quality) and three output constructs (Attitude, Behavioural Intention to Use, and Intention to Recommend e-public services) using an SEM and several supervised ML models (AlHadid et al. 2022). Their results revealed that only Perceived Risk had no direct and significant positive relationship with customer attitudes towards e-public services.

Nugroho et al. investigated the impact of UMEGA variables on public acceptance of a new mobile application for population administration and civil registration in Indonesia (Nugroho et al. 2022). Their results showed that two factors, Effort Expectancy and Perceived Risk, had a significant influence on user attitudes towards using the new application. Its public adoption was unaffected by Performance Expectancy or Social Influence.

Garcia-Rio et al. surveyed theoretical models based on UMEGA, including the role of Spanish e-government in the context of the COVID-19 pandemic (Garcia-Rio et al. 2023). According to the results, Performance Expectancy was the most crucial factor for users when considering e-public services, followed by Social Influence, Role of e-Government during the health crisis, and Perceived Trust.

3.2. Comparison of Existing Models of Customer Satisfaction with E-Government Services

The related work summarized in the previous subsection draws on factors derived from seminal works in the field of TAM and UTAUT from Davis (Davis 1989) and Venkatesh et al. (Venkatesh et al. 2003) respectively. The majority of these studies have utilized Partial Least Squares (PLS) SEM, while four models have been built using service evaluation approaches (Papadomichelaki and Mentzas 2012; Mensah et al. 2020; Nugroho et al. 2022; Garcia-Rio et al. 2023). One study relied on SEM and ML techniques (classification) (AlHadid et al. 2022). The main features of adoption models for e-public services described above are outlined in Table 2.

The distribution of input factors in the described models is as follows: Perceived Usefulness (10/10), Perceived Ease of Use (10/10), Social Influence (7/10), Facilitating Conditions (4/10), Trust (4/10), Risk (4/10), and Service Quality (2/10). The effectiveness of the models proposed in the literature varies from 38.0% (Camilleri 2020) to 74.0% (Xie et al. 2017), with the number of latent variables ranging from 2 to 8. The number of statistically significant factors varies between 2 and 7.

Despite numerous studies identifying the factors influencing customer satisfaction with e-public services, establishing universally accepted metrics for assessing the effectiveness of these services remains challenging. Furthermore, current research on the aspects of e-public services adoption within the EU e-governance environment is limited in scope and overlooks the evolving landscape of consumer preferences, behaviours, and habits. Consequently, there is a need for new methodologies and empirical inquiries to bridge

existing gaps in order to provide helpful dependencies for policymakers, public authorities, and their service providers.

Table 2. Comparison of models of customer attitude and intention to use e-government services.

Reference	Theoretical Foundation	Evaluation Metrics (Number)	Statistically Significant Factors (Number)	R^2
(Davis 1989)	MLR	Usefulness, Ease of Use (2)	Usefulness (1)	0.31–0.74
(Venkatesh et al. 2003)	PLS-SEM	Effort Expectancy, Performance Expectancy, Social Influence, Facilitating Conditions (4)	Effort Expectancy, Performance Expectancy (2)	0.36–0.77
(Papadomichelaki and Mentzas 2012)	e-GovQual	Ease of Use, Trust, Functionality of the Interaction Environment, Reliability, Content and Appearance of Information, Citizen Support (6)	Efficiency, Reliability, Citizen Support, Trust (4)	0.547
(Xie et al. 2017)	TAM, TPB, UTAUT, Trust, Risk	Perceived Usefulness, Perceived Ease of Use, Trust, Risk (4)	Perceived Usefulness, Perceived Ease of Use, Trust, Risk (4)	0.740
(Kurfali et al. 2017)	UTAUT, Trust	Perceived Usefulness, Perceived Ease of Use, Social Influence, Facilitating Conditions, Trust (5)	Perceived Usefulness, Social Influence, Facilitating Conditions, Trust (4)	0.584
(Lallmahomed et al. 2017)	UTAUT2, GAM	Perceived Usefulness, Perceived Ease of Use, Social Influence, Facilitating Conditions, Perceived Price Value, Computer Self Efficacy, Trustworthiness (7)	Perceived Usefulness, Facilitating Conditions, Perceived Price Value, Computer Self Efficacy, Trustworthiness (5)	0.380
(Mensah et al. 2020)	UMEGA	Perceived Usefulness, Perceived Ease of Use, Social Influence, Perceived Risk (4)	Perceived Risk (1)	0.626
(Camilleri 2020)	TAM	Perceived Usefulness, Perceived Ease of Use, Social Influence, Facilitating Conditions (4)	Perceived Usefulness, Perceived Ease of Use, Social Influence, Facilitating Conditions (4)	0.380
(ElKheshin and Saleeb 2020)	TAM	Perceived Usefulness, Perceived Ease of Use (2)	Perceived Usefulness, Perceived Ease of Use (2)	0.604
(AlHadid et al. 2022)	TAM, TPB, UTAUT, Trust, Risk, ML	Perceived Usefulness, Perceived Ease of Use, Social Influence, Facilitating Conditions, Trust, Risk, Service Quality, Reliability (8)	Perceived Usefulness, Perceived Ease of Use, Social Influence, Facilitating Conditions, Trust, Service Quality, Reliability (7)	0.485
(Nugroho et al. 2022)	UMEGA	Perceived Usefulness, Perceived Ease of Use, Social Influence, Perceived Risk (4)	Perceived Ease of Use, Perceived Risk (2)	0.389
(Capgemini et al. 2023)	UMEGA	Perceived Usefulness, Perceived Ease of Use, Social Influence, Perceived Trust (4)	Perceived Usefulness, Social Influence (2)	0.694

3.3. Main Factors Affecting Consumer Attitudes and Intention to Adopt E-Government Services

According to the previous studies, the main factors influencing the adoption of electronic government services can be reflected in a theoretical model with the following seven constructs: Perceived Usefulness, Perceived Ease of Use, Social Influence, Facilitating Conditions, Perceived Trust, Perceived Risk, and Service Quality. The proposed combination integrates both internal (Perceived Usefulness, Perceived Ease of Use, Perceived Trust, Perceived Risk, Service Quality) and external (Social Influence, Facilitating Conditions) constructs shaping citizen attitudes and intention to use e-public services.

1.   Perceived Usefulness

Perceived Usefulness (Davis 1989) of electronic administrative services refers to the practical value and benefits that digital platforms and technologies bring to the delivery and utilization of government services. E-administrative services, often accessible through online systems and mobile applications, streamline bureaucratic processes and offer citizens and businesses quick access to various digital government services. This dimension encompasses factors such as timesaving, reduced paperwork, and increased transparency in administrative procedures (Al-Sakran and Alsudairi 2021; Cheng et al. 2021). The goal is to create a more citizen-centric, responsive, and efficient administrative ecosystem that leverages technology to facilitate interactions between the government and its citizens.

2.   Perceived Ease of Use

Perceived Ease of Use (Davis 1989) in e-public services is the subjective assessment by users of how straightforward and convenient it is to interact online with government services. This concept, often associated with user experience and human–computer interaction, gauges the user's perception of the simplicity and accessibility of digital platforms or channels for public services. A higher Perceived Ease of Use implies that individuals find the processes intuitive, user-friendly, and navigable, leading to a positive user experience (Medina-Quintero et al. 2021).

3.   Social Influence

Social Influence on e-government evaluates the impact of societal factors, interactions, and collective opinions on individuals' behaviours and decisions regarding the utilization of government services. It reflects how the perceptions, recommendations, or experiences of others within user social networks influence his/her decision to adopt public services. Positive Social Influence may arise from positive reviews, word-of-mouth recommendations, or shared favourable experience encouraging individuals to use digital platforms for public services. Social Influence is important for the adoption of e-public services, as it fosters a positive collective perception within the broader community (Junnonyang 2021).

4.   Facilitating Conditions

Facilitating Conditions relate to external factors and resources that contribute to the ease and effectiveness of using e-public services. This TAM concept includes elements such as the availability of necessary infrastructure, user-friendly technologies, and accessible support systems. Adequate technical support, clear guidelines, and a supportive regulatory framework ensure that citizens can navigate and utilize these services with confidence (Camilleri 2020).

5.   Perceived Trust

Perceived Trust as a part of extended UTAUT models measures the subjective assessment by individuals of the reliability, integrity, and security of government-provided digital services. It encapsulates citizens' confidence in the government's ability to handle their data securely, deliver services transparently, and act in their best interests. Factors contributing to Perceived Trust include data protection measures and the overall credibility of the government in safeguarding user data. Building and maintaining trust is a critical element in promoting citizen engagement and satisfaction with the e-services offered by government agencies (Pedrosa et al. 2022; Shayganmehr et al. 2023).

6.   Perceived Risk

Perceived Risk is a metric for individuals' subjective assessments of potential threats, uncertainties, or concerns associated with digital interactions in government platforms. Perceived risks may include uncertainties about the effectiveness of digital systems, fear of technical issues, or concerns about the safety and privacy of online transactions. Transparent data protection policies, robust cybersecurity measures, and effective communication strategies can reduce the perceived risks among citizens (Fakhruzzaman and Dimitrova 2020; Li 2021).

7. Service Quality

The quality of e-government services encompasses two aspects: tangibles and reliability. The first includes physical aspects that contribute to the overall quality of service delivery—the appearance of government service platforms, usability of online systems, clarity of information provided, and availability of supplementary materials. Well-designed and user-friendly interfaces and well-maintained digital services contribute to a positive service experience (Uchenna 2020). On the other hand, reliability pertains to the consistency of e-government services, emphasizing accuracy and timeliness. Ensuring reliability is important for a positive perception of government's ability to meet citizens' needs (Li and Shang 2020).

These factors underscore the complex nature of consumer perception towards e-public services. In the subsequent section, we evaluate the strength of these factors in influencing customer attitude towards e-public services. The impact of these constructs on customer behaviour is dependent on other parameters, including the influence of the broader business environment. Providers of e-public services can leverage these factors to build positive customer experience and foster long-term user loyalty.

4. Materials and Methods

The main objective of our research methodology was to identify and clarify customer perceptions of e-administrative services while anticipating their future changes. Therefore, we started our research by gathering a primary dataset. The questionnaire focused on the new e-portal (https://portal.nra.bg) (accessed on 5 March 2024) of the National Revenue Agency (NRA). The agency's portal, released at the end of 2022, includes enhanced features such as direct identification, a redesigned interface, additional functionalities, more intuitive navigation, and convenient access to user information. In December 2022 alone the new portal processed over 75 thousand additional requests, resulting in a significant increase in revenue for the agency (Stoyanova and Popova 2023).

To systematically analyse the gathered customer data, we employed descriptive (statistical) and predictive ML analytic techniques, SEM, and multi-criteria decision-making. The combination of SEM with ML methods can uncover complex dependencies in customer attitudes towards e-government services. The developed ML models, including both unsupervised (cluster formation) and supervised (predictive) models, can add value by enhancing the understanding of these relationships, providing a more comprehensive view of the factors influencing user perception. For example, SEM results reveal relationships between latent variables, while cluster analysis generates insights into different customer segments. In predicting customer attitudes towards e-government services, ML methods such as SVM, Decision Tree, Random Forest, and AdaBoost offer several advantages. While SEM uncovers the strength and direction of relationships between latent and observed variables, ML methods offer predictive capabilities based on the constructs identified by SEM. The third element in our methodology, MCDM methods, can utilize SEM coefficients in complex criteria indexes for evaluation of e-government services. This integrated approach enhances the understanding of complex patterns and interactions within user datasets, offering a holistic approach to analysing customer attitude towards e-government services.

In data processing, we followed the steps of the standard algorithms for data analysis. Performing sentiment analysis on respondents' opinions allowed us to identify common issues users may face with e-administrative services. The obtained outcomes about customers' perception and usage of e-administrative services can enable vendors to effectively address users' concerns and tailor their marketing strategies accordingly.

4.1. Designing the Questionnaire and Collecting Data

The survey method was chosen as the research instrument for its ability to gather a substantial amount of data for analysing citizen behaviour and intentions regarding digital public services. An online questionnaire was designed to collect data on user perceptions of e-public services. It was based on previous research on citizen intentions to use digital

public services (AlHadid et al. 2022; Xie et al. 2017; Kurfali et al. 2017; Mensah et al. 2020; Camilleri 2020; ElKheshin and Saleeb 2020; Nugroho et al. 2022; Garcia-Rio et al. 2023) and followed the format proposed by Al Hadid et al. (AlHadid et al. 2022).

The questionnaire consisted of five main parts: introduction, demographics, experience with e-administrative services, attitude toward these services, and future intentions. The four constructs from Question #10 (Perceived Usefulness), Question #11 (Perceived Ease of Use), Question #12 (Social Influence), and Question #13 (Facilitating Conditions) were adopted from Li (Li 2021), while items for Question #17 (Perceived Trust) and Question #18 (Perceived Risk) were retrieved from Xie et al. (Xie et al. 2017). Question #19 and Question #20, which measured service quality tangibles and reliability, utilized five items obtained from Alkraiji and Ameen (Alkraiji and Ameen 2021). Three items each for Question #14 (Attitude) and Question #15 (Intention to Use the portal) were adapted from Xie et al. (Xie et al. 2017). To account for Intention to Recommend the portal (Question #16), a multiple choice grid was added based on suggestions offered by Talukder et al. (Talukder et al. 2019). Details about the study and the link to the questionnaire were distributed through partner organizations using various communication channels.

4.2. Measuring and Scaling the Questionnaire

Approximately half of the survey questionnaire (11 out of 21) were composed of "multiple choice grid" questions, which implemented a five-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). A further 29% of the questionnaire (6 out of 21) comprised "single choice" questions. Two questions required open-ended text responses to be entered into text fields respectively marked as "short answer" and "paragraph" type in Google Forms. Finally, two questions were formulated using checkboxes.

4.3. Data Analysis Methods

Data analysis methods for the adoption of e-government services can be categorized into three groups: classical statistical methods, intelligent methods, and hybrid methods that combine techniques from the previous two groups. The first category encompasses methods that measure object properties, summarize and visualize the main characteristics of the sample, and test relationships between items and groups.

Intelligent methods, such as SEM, decision trees, neural network analysis, and sentiment analysis, reveal hidden relationships between variables. SEM, a widely utilized methodology for studying complex systems where factors cannot be directly evaluated, consists of statistical techniques for testing research hypotheses and measuring and analysing relationships between input and output variables (Beran and Violato 2010). Neural networks and decision trees, as data mining techniques, are used to predict respondent behaviour, while sentiment analysis extracts and analyses subjective attitudes from text opinions. Intelligent ML methods can uncover unknown patterns and relationships between variables that may not be apparent when using classical statistical methods.

5. Results

The methodology outlined in Section 4 was employed step-by-step to address the research tasks.

5.1. Customer Data Collection

We shared a link to the online survey through our institutional websites, social media (Facebook groups), and emails. The survey targeted Bulgarian users of online public services and was completed on a voluntary basis. Created using Google Forms, the survey consisted of 21 questions designed to measure customers' perceptions toward e-public services (Ilieva et al. 2024). The respondents' data were collected from 18 January 2023 to 22 May 2023. A total of 258 participants completed the questionnaire, of whom 64 indicated that they do not use online administrative services (Question #7). A duplicate check was performed, and there were no identical values found in the dataset rows. However, the

data on model constructs (from Question #10 to Question #20) showed that there were eight duplicates of two dataset rows, as follows: (#40, #81, #139, #148, #150, #160), (#119, #124, #128, #156) (see Figure 1).
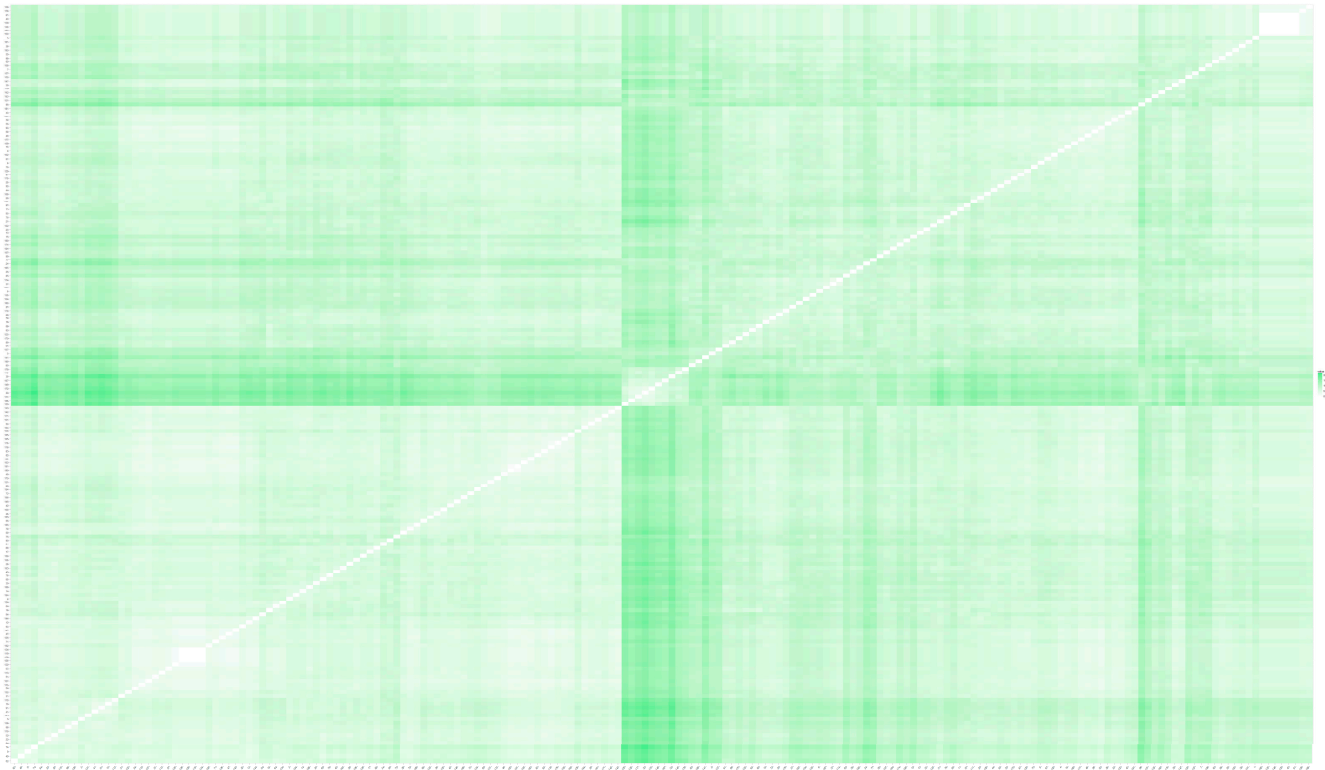
Figure 1. The matrix of distances (ordered dissimilarity matrix) between respondents' answers.

Figure 1 illustrates the degree of similarity between the respondents' answers, with closer distances indicating smaller differences. The degree of similarity is represented by different colours, ranging from full coincidence (0—white) to maximum difference (20—light green). Because the dataset did not contain identical records, all observations are included in the analysis.

Data storage

The questionnaire and respondents' dataset are available online (Ilieva et al. 2024).

Data encoding

The rules for coding and coded data are also available online. Out of all 21 responses, 19 have been coded (Ilieva et al. 2024). The remaining two open-text answers (municipality and opinions) have been additionally processed.

Data preprocessing

Preprocessing was carried out and the dataset quality was examined for accuracy and consistency.

5.2. Statistical Analysis

To clarify the profile of the participants in the survey, a classical statistical analysis (percentage distribution of responses, descriptive statistics, and correlation analysis) was performed.

Main Characteristics of the Sample

Table 3 illustrates the demographics of the questionnaire respondents. A significant majority of the participants were female, accounting for 74% of the total number of partici-

pants (Question #1). More than three quarters (77%) of the respondents were under the age of 40 (Question #2). The sample was dominated by individuals with at most a high school degree, comprising 59.3% of the participants (Question #6). The survey was primarily conducted in urban areas, with 95.7% of the respondents residing in such locations (Question #3).

Table 3. User profile of the sample (*n* = 258).

| Variables of the Sample		No. of Respondents	Percentage (%)
1. Gender	Male	66	25.6
	Female	192	74.4
2. Age	Under 20	77	29.8
	Between 21 and 30	87	33.7
	Between 31 and 40	35	13.6
	Between 41 and 50	43	16.7
	Over 50	16	6.2
3. Place of residence	City	161	62.4
	Town	86	33.3
	Village	11	4.3
4. Municipality/Province	-	-	-
5. Monthly income per household member	Less than BGN 1320	140	54.3
	More than BGN 1320	118	45.7
6. Education	High school	153	59.3
	Bachelor	59	22.9
	Master	42	16.3
	PhD	4	1.6
7. Do you use electronic administrative services?	No	64	24.8
	Yes	194	75.2

The geospatial distribution of participants (Question #4) reveals that the majority were from the Plovdiv district (71.6% of the survey participants). The second highest proportion of respondents were from the Pazardzhik district (6.2% of the total), followed by the Sofia city district with 5.2% of sample size. The survey primarily targeted the Southern Central region, comprising 83.5% of participants, followed by the Southwestern and Southeastern regions, each representing 6.2%.

For 75% of the participants, online administrative services were the preferred form of communication with public authorities (Question #7). This percentage is relatively close to the adoption rate of digital public services as reported in a national survey conducted at the beginning of 2023 (NCPS 2023).

The most widely utilized e-public services at the territorial level encompass those associated with local taxes and fees and civil status, representing 40.4% and 26.0%, respectively (Question #8). At the national level, the most commonly used e-services include social security for employees, corporate taxes, and value-added tax, constituting 23.3%, 22.0%, and 19.8%, respectively (Question #9).

Feature Selection

The colour depth of the heat maps in Figures 2 and 3 represents standardized values, ranging from a minimum of −2.92 (white) to a maximum of 1.95 (green). The dendrogram at the top of Figure 2 illustrates the grouping of respondents based on similarities in their e-government attitudes. Additionally, the variable structure in Figure 3 (right) underscores their similarities. Both heat maps visually display clusters of observations and variables sharing similar characteristics with no unusual or unexpected patterns.
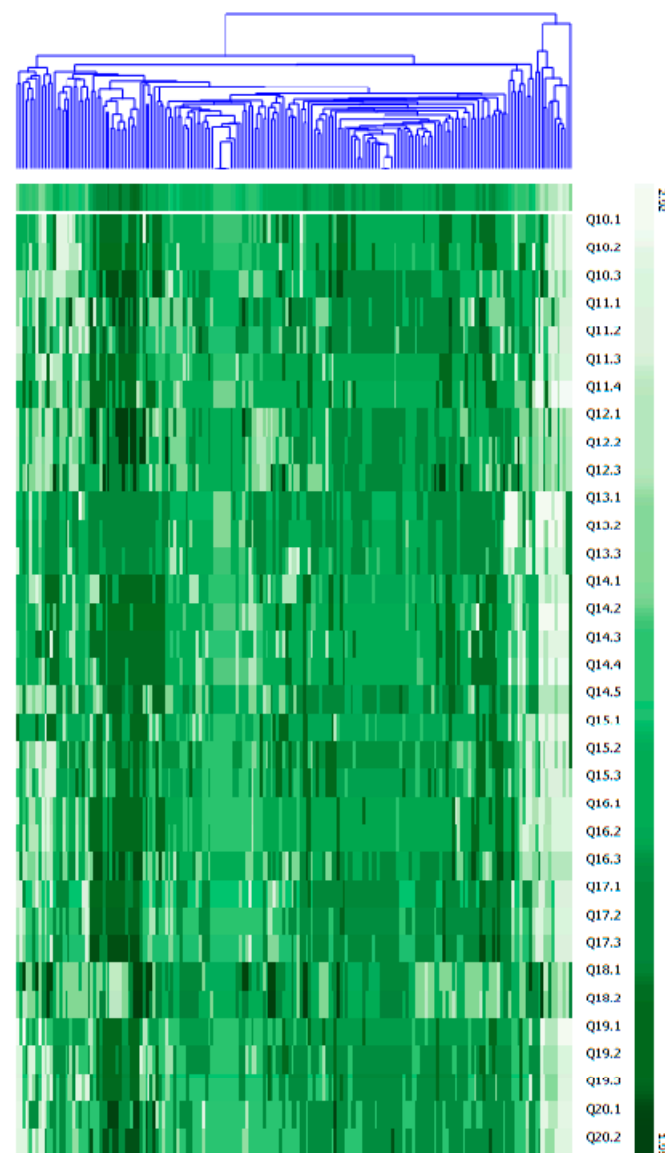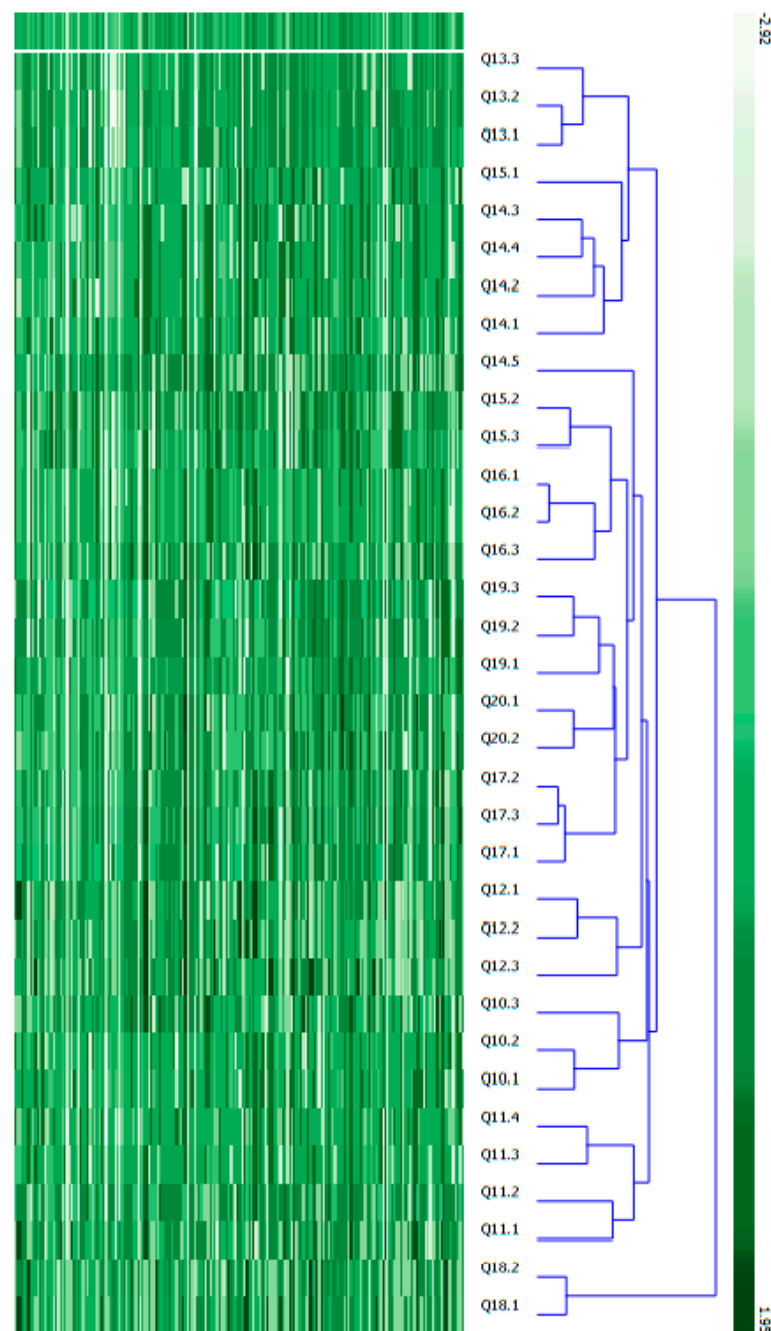
Figure 2. Hierarchical group heat map by respondents.

Clustering

To identify the groups of users with similar characteristics and the variables that have a comparable effect on attitudes toward e-government, we employed the *k*-means method for cluster analysis. The optimal number of clusters was determined using the Elbow and Silhouette methods, with the results indicating that this number is 2 (Figure 4). The two clusters consisted of 62 and 132 respondents, respectively.

The smaller cluster (Cluster #1) comprises dissatisfied e-government users with a less positive attitude towards e-public service adoption, as reflected by lower ratings in Attitude (Question #14), Intention to Use (Question #15), and Intention to Recommend (Question #16) e-government services (Table 4). The indicators with the most significant influence on overall dissatisfaction are Trust (Question #17), Service Quality (Question #19–Question #20), and Perceived Usefulness (Question #10). In contrast, the second cluster, consisting of the majority of users, demonstrates a higher level of satisfaction with digital public services. Perceived Ease of Use (Question #11) and Perceived Risk (Question #18) are the most significant factors contributing to the positive attitude of this second group of users. Table 4 presents the average values of the indicators for the two clusters along with the differences between these estimates.

Figure 3. Hierarchical group heat map by factors.

Sentiment Analysis

The open-ended question (Question #21) received 54 text replies. After preprocessing and filtering, 35 responses concerning e-public services were kept. The average sentiment scores for responses were as follows: positive—22 (63%, average: 0.712), neutral—5 (14%, average: 0.519), and negative—8 (23%, average: 0.218). These results indicate that respondents generally support e-government services as a convenient means of interacting with public administration, highlighting some of the advantages. Those expressing a negative attitude primarily had concerns about complex website navigation and potential security issues. Neutral opinions supported the usage of e-public services but highlighted weaknesses in online data processing.
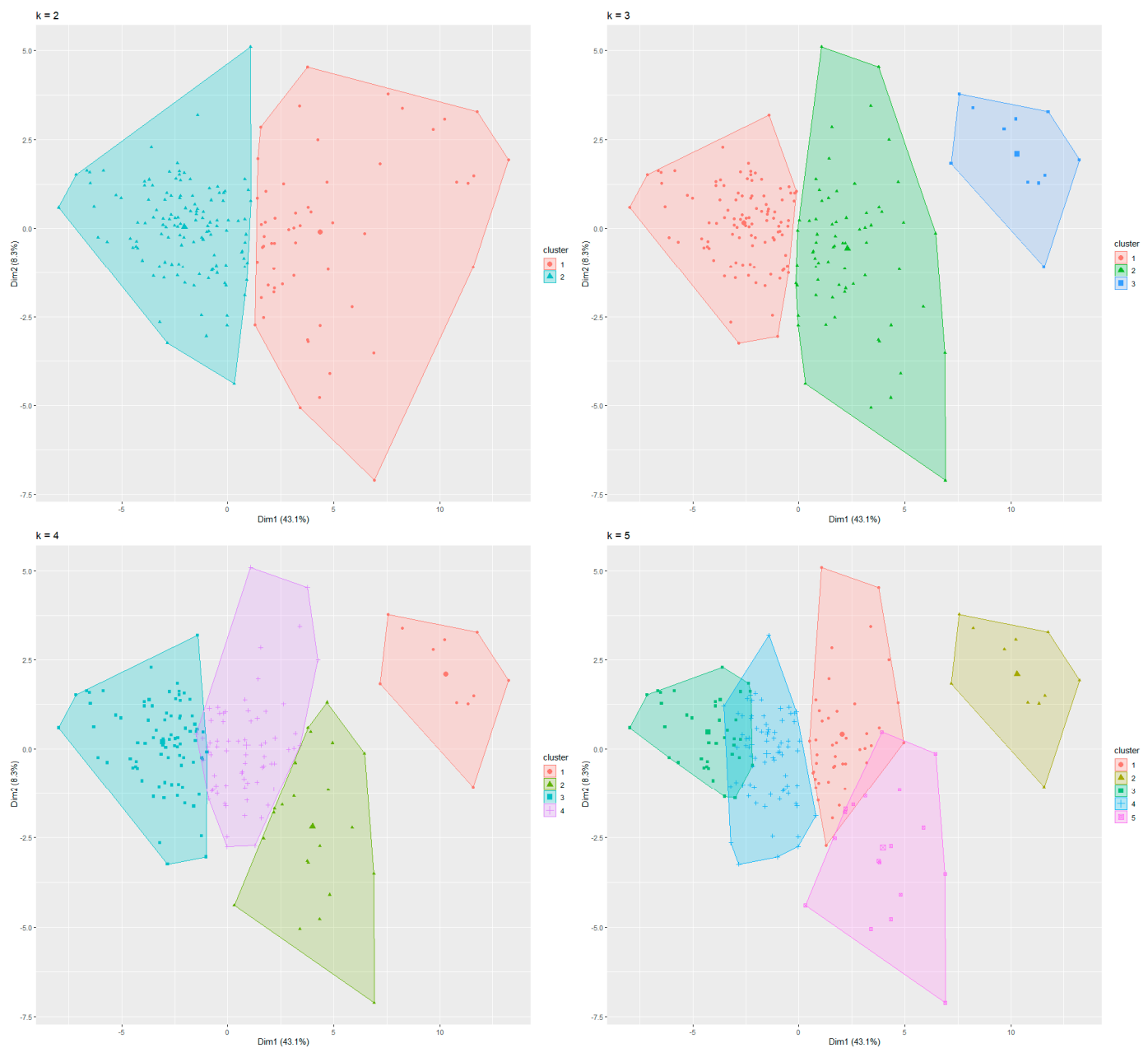
Figure 4. Users' clusters by *k*-means (*k* = 2, 3, 4, 5) using 34 input indicators.

The respondents proposed the following recommendations for e-service improvements:

- Online systems could provide technical support to users and response to user queries in real time;
- The structure and navigation system of websites could be optimised;
- The citizens' easy access to e-services could be ensured without additional requirements, such as electronic signatures or training in accounting;
- Cybersecurity measures and data protection could be strengthened.

The recommended actions aim to facilitate users' acceptance and utilization of e-government services. Enhancing the benefits of online systems and improving responsiveness aligns with the principle of Ease of Use by promoting a more user-friendly experience. Improving website organization and navigation corresponds to Effort Expectancy by simplifying user interactions. The suggestion to ensure easy accessibility without complex

prerequisites aligns with Facilitating Conditions, specifically reducing barriers to entry. Strengthening cybersecurity addresses concerns about Perceived Risk, mitigating users' apprehensions about potential security issues. Collectively, these recommendations contribute to a positive user experience and acceptance of e-government services based on UTAUT principles.

Table 4. Average values by cluster and absolute differences between clusters by indicators.

	Q10.1	Q10.2	Q10.3	Q11.1	Q11.2	Q11.3	Q11.4	Q12.1	Q12.2
Cluster #1	2.968	2.903	2.371	2.661	2.629	2.823	3.097	2.274	2.145
Cluster #2	4.144	4.114	3.568	3.424	3.614	3.985	4.136	3.402	3.364
Difference	−1.176	−1.211	−1.197	−0.763	−0.985	−1.162	−1.039	−1.128	−1.219
	Q12.3	**Q13.1**	**Q13.2**	**Q13.3**	**Q14.1**	**Q14.2**	**Q14.3**	**Q14.4**	**Q14.5**
Cluster #1	2.355	3.387	3.387	3.129	2.903	2.919	2.968	2.935	2.274
Cluster #2	3.333	4.576	4.417	4.220	3.947	4.205	4.129	4.212	3.530
Difference	−0.978	−1.189	−1.030	−1.091	−1.044	−1.286	−1.161	−1.277	−1.256
	Q15.1	**Q15.2**	**Q15.3**	**Q16.1**	**Q16.2**	**Q16.3**	**Q17.1**	**Q17.2**	**Q17.3**
Cluster #1	3.081	2.613	2.710	2.500	2.500	2.177	2.371	2.500	2.371
Cluster #2	3.947	3.848	3.955	4.076	4.091	3.432	3.788	3.879	3.735
Difference	−0.866	−1.235	−1.245	−1.576	−1.591	−1.255	−1.417	−1.379	−1.364
	Q18.1	**Q18.2**	**Q19.1**	**Q19.2**	**Q19.3**	**Q20.1**	**Q20.2**		
Cluster #1	3.097	2.839	2.823	2.565	2.419	2.629	2.452		
Cluster #2	3.114	3.068	3.977	3.856	3.742	3.697	3.765		
Difference	−0.017	−0.229	−1.154	−1.291	−1.323	−1.068	−1.313		

5.3. SEM Model of Customer Attitudes towards E-Government Services

The assessment of consumer attitudes towards adoption of e-public services lacks consensus on defining inputs and outputs, as highlighted in the review of previous similar research (Section 3). To address this issue, we iteratively employed the SEM method using SmartPLS 3 software (Ringe et al. 2015).

The algorithm used for structural regression modelling involved the following five steps:

1. Formulate hypotheses about constructs and their interrelationships.
2. Identify indicators for each construct.
3. Execute the modelling procedure and assess the model fit.
4. Evaluate the quality of the model; if satisfactory, proceed to Step 5, otherwise return to Step 3 to enhance the model.
5. Discuss the obtained results.

In Step 1, hypotheses about model constructs and their interrelationships are formulated, guided by the comparison of existing models for user attitudes towards e-public services (Table 2) (AlHadid et al. 2022).

H₁: *There is a significant impact of Perceived Usefulness on Attitude towards e-government services.*

H₂: *There is a significant impact of Perceived Ease of Use on Attitude towards e-government services.*

H₃: *There is a significant impact of Social Influence on Attitude towards e-government services.*

H₄: *There is a significant impact of Facilitating Conditions on Attitude towards e-government services.*

**H₅:** *There is a significant impact of Perceived Trust on Attitude towards e-government services.*

H₆: *There is a significant impact of Perceived Risk on Attitude towards e-government services.*

H₇: *There is a significant impact of Service Quality on Attitude towards e-government services.*

H₈: *Demographic characteristics have a statistically significant impact on customer satisfaction with e-government services (AlHadid et al. 2022). The demographic characteristics include Gender, Age, Residence, Income and Education level.)*

Step 2. Identify indicators for each construct.

The indicators of latent variables (8 constructs and 28 variables) were derived from the survey questionnaire (Ilieva et al. 2024). The measurement model consisted of 23 input indicators: PU1, PU2, and PU3 from the Perceived Usefulness (PU); PE1, PE2, PE3, and PE4 from Perceived Ease of Use (PE); SI1, SI2, and SI3 from Social Influence (SI); FC1, FC2, and FC3 from Facilitating Conditions (FC); PT1, PT2, and PT3 from Perceived Trust (PT); PR1 and PR2 from Perceived Risk (PR); SQT1, SQT2, SQT2, SQR1, SQR2, and SQR3 from Service Quality (SQ); and five output indicators, ATT1, ATT2, ATT3, ATT4, and ATT5, from the output construct Attitude towards e-Government Services (ATT), represented in Figure 5.
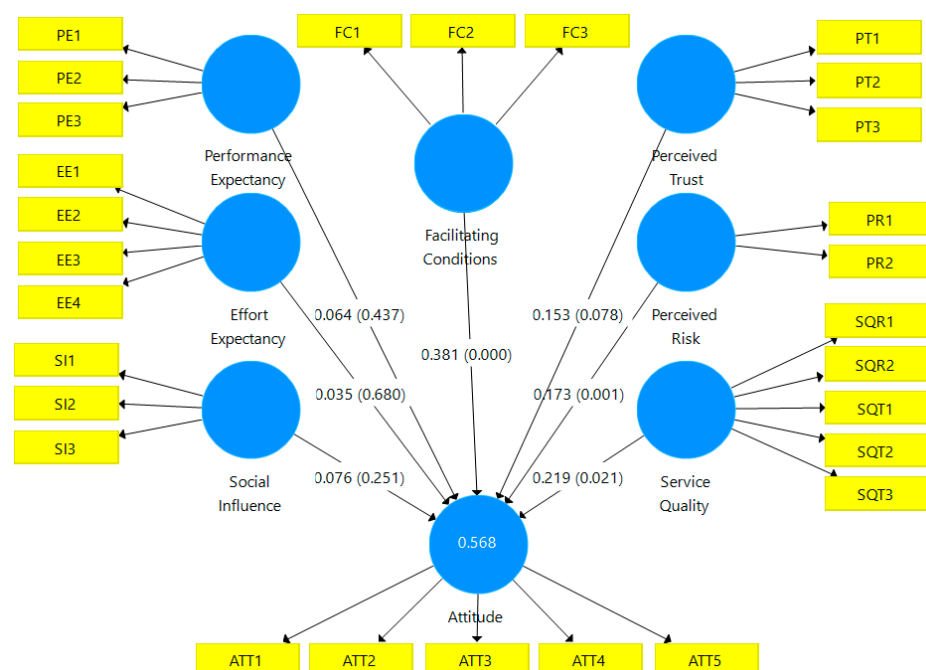
Figure 5. Measurement model with six latent variables along with their path coefficients and *p*-values.

Step 3. Execute the modelling procedure and assess the model fit.

The PLS algorithm has been employed and model parameters have been obtained.

Step 4. Evaluate the quality of the model. If satisfactory, proceed to Step 5; otherwise, return to Step 3 to enhance the model.

Based on evaluation of the path coefficients, the model does not align well with the dataset. This discrepancy arises from the *p*-values of Perceived Usefulness, Perceived Ease of Use, and Social Influence (0.437, 0.680, and 0.251, respectively), which exceed the acceptable threshold (Figure 5). Consequently, the process returns to Step 3 and modifies the model settings by eliminating certain factors. Now, the *p*-values of the path coefficients for the new model are acceptable, and the model examination continues to establish the validity and reliability of the constructs (Step 4).

Construct Validity and Reliability

The initial phase of the validity check requires assessing both the measurement model and the structural model. The measurement model evaluates the validity and reliability of the constructs; this evaluation encompasses evaluating the reliability of the constructs and indicators along with the convergent validity and discriminant validity of the latent

variables. The structural model is essential for determining the significance of the proposed hypotheses.

Factor Loadings

Factor loadings measure the extent to which each item in the correlation matrix is linked to the specified principal component. In our model, all items demonstrate factor loadings surpassing the recommended threshold of 0.5 suggested by Hair et al. (Hair et al. 2014). Figure 6 and Table 5 display the model's factor loadings.
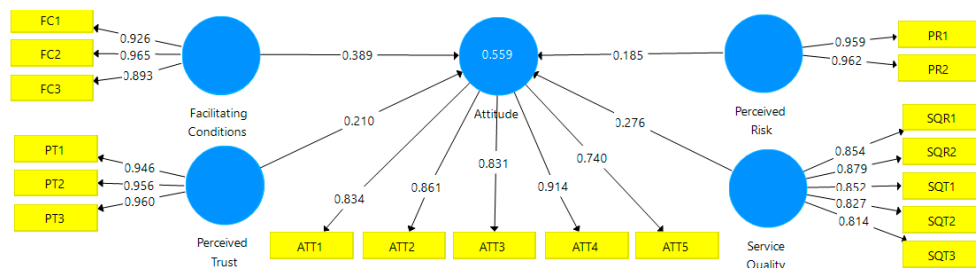
Figure 6. SEM procedure results, showing the regression coefficient for each construct and the coefficient of determination.

Table 5. Factor loadings for indicators.

Indicator Variable	Factor Loading	Indicator Variable	Factor Loading	Indicator Variable	Factor Loading	Indicator Variable	Factor Loading
ATT1	0.834	FC1	0.926	PT1	0.946	SQT1	0.852
ATT2	0.861	FC2	0.965	PT2	0.956	SQT2	0.827
ATT3	0.831	FC3	0.893	PT3	0.96	SQT3	0.814
ATT4	0.914	PR1	0.959	SQR1	0.854		
ATT5	0.740	PR2	0.962	SQR2	0.879		

Indicator Multicollinearity

To assess the multicollinearity among indicators, the Variance Inflation Factor (VIF) statistic was calculated. A VIF value below five is considered acceptable, indicating acceptable multicollinearity (Fornell and Bookstein 1982). Table 6 presents the VIF values, demonstrating that each indicator has a VIF below the recommended threshold.

Table 6. Construct reliability (DG rho and CR), convergent validity (AVE), and multicollinearity (VIF).

Factor	DG rho	CR	AVE	VIF
Perceived Risk	0.917	0.960	0.922	1.079
Perceived Trust	0.951	0.968	0.910	2.391
Facilitating Conditions	0.924	0.949	0.862	1.341
Service Quality	0.914	0.926	0.715	2.217
Attitude	0.898	0.921	0.702	

DG rho: Dillon–Goldstein's rho (>0.7), CR: Composite Reliability (>0.6); AVE: Average Variance Extracted (>0.5); VIF: Variance Inflation Factors (<5).

Reliability Analysis

To assess construct reliability, two main methods—Dillon–Goldstein's rho (DG rho) and Composite Reliability (CR)—were applied for measuring repeatability. To ensure adequate reliability, both the DG rho and CR values should surpass 0.7 (Fornell and Bookstein 1982). The DG rho values ranged from 0.898 to 0.951, while the CR values

ranged from 0.921 to 0.968 (Table 6). Consequently, the DG rho and CR values for all latent variables in the model are acceptable, indicating reliable coefficients for all constructs.

Construct validity requires two types of validity assessment: convergent validity and discriminant validity.

Convergent Validity

Convergent validity refers to the level of consistency among multiple measures of the same concept. To assess the convergent validity of the construct, the average variance extracted (AVE) was calculated, with a minimum threshold of 0.5 (Fornell and Bookstein 1982). The AVE scores for all constructs were statistically significant, indicating the strong convergent validity of our model (Table 6).

Discriminant Validity

Discriminant validity refers to the degree to which measures of distinct concepts can be distinguished from each other.

Heterotrait–Monotrait Ratio (HTMT)

To assess discriminant validity, the HTMT (Heterotrait–Monotrait) ratio calculates the correlation between constructs. The threshold for HTMT varies in the literature, typically falling between 0.85 and 0.9. The results for our model, outlined in Table 7, show that the HTMT ratios for the constructs are below the specified threshold of 0.85 and are statistically significant.

Table 7. Discriminant validity—HTMT.

Factor	ATT	FC	PR	PT	SQ
Attitude					
Facilitating Conditions	0.669				
Perceived Risk	0.193	0.033			
Perceived Trust	0.623	0.520	0.145		
Service Quality	0.67	0.473	0.082	0.774	

Assessment of Structural Model

The *p*-values of the model constructs indicate a significant impact on user attitudes towards e-public services, with values below 1% for Facilitating Conditions, Perceived Risk, and Service Quality and below 5% for Perceived Trust, as shown in Figure 7 and Table 8. These findings align with hypotheses H_4–H_7 and previous similar research. The regression coefficients for all input factors are positive.
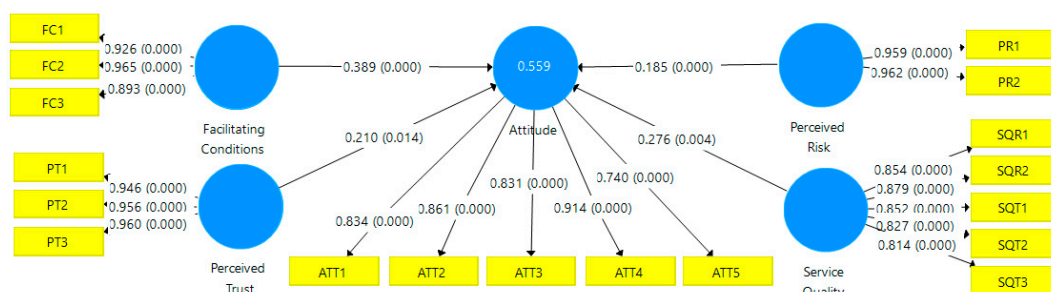
Figure 7. Path coefficients and *p*-values—inner and outer model.

Table 8. The path coefficient of the relationship between latent variables.

Hypothesis	β	Sample Mean	Mean	SD	t Statistics	p Values	R^2	f^2	Q^2
H$_4$ Facilitating Conditions $\rightarrow$ Attitude	0.389	0.389	0.387	0.078	4.972	0.000		0.256	
H$_5$ Perceived Risk $\rightarrow$ Attitude	0.185	0.185	0.182	0.051	3.628	0.000	0.559	0.072	0.385
H$_6$ Perceived Trust $\rightarrow$ Attitude	0.210	0.21	0.204	0.085	2.461	0.014		0.042	
H$_7$ Service Quality $\rightarrow$ Attitude	0.276	0.276	0.284	0.094	2.921	0.004		0.078	

Regarding the obtained structural model, the pathways FC $\rightarrow$ ATT and SQ $\rightarrow$ ATT express relatively large effects, while the PT $\rightarrow$ ATT and PR $\rightarrow$ ATT relationships demonstrate weak influences.

Step 5. Discuss the obtained results.

The reasons for rejecting the effects of Perceived Usefulness (H$_1$), Perceived Ease of Use (H$_2$), and Social Influence (H$_3$) on User Attitude towards e-government services (Figure 5) can be explained based on the specific context of our study. The new portal of the NRA has been developed using the latest IT technologies, which has changed supposed user perceptions. Users do not consider Perceived Usefulness as a critical factor due to the high level of maturity of the new portal. Additionally, the electronic equivalents of NRA public services have been available since 2012 and are well-established, leading to the rejection of Perceived Ease of Use as an influence on User Attitude. Furthermore, as users have accumulated sufficient experience with the portal, the influence of social networks has decreased. Consequently, H$_3$, which pertains to Social Influence, is not supported in our findings.

Our results are consistent with those obtained by Mensah et al. (2020) in their study on the adoption of Chinese e-government services. Both studies reject the significance of the same three factors—Perceived Usefulness, Perceived Ease of Use, and Social Influence (Table 2). One possible reason for this this alignment is the fact that both Bulgaria and China have developed e-government systems, ranked in the VHEGDI group according to the last UN survey (UN DESA 2022). However, results from a previous study by Xie et al. (Xie et al. 2017), conducted in China five years earlier, show a different outcome, with these three factors significantly influencing user attitudes towards e-government services. This difference supports our assumption regarding the impact of IT maturity. Additionally, Table 2 indicates that in some countries less developed in information technologies these three factors only partially influence user attitudes towards e-government services (ElKheshin and Saleeb 2020; Nugroho et al. 2022).

In the fitted SEM model, Facilitating Conditions (H$_4$) demonstrated the strongest positive relationship (Figure 7, $\beta = 0.389$, $p < 0.001$) with attitude towards e-public services. For citizens, Facilitating Conditions encompass access to technological resources along with the provision of technical support, aiding them during transactions with e-government. The robust impact of Facilitating Conditions indicates that available telecommunication services, software quality, a mobile-friendly interface, and accessible support systems can enhance customer satisfaction. This finding aligns with the results of previous similar studies by Kurdafi et al., Camilleri, AlHadid et al., Nugroho et al., and Garcia-Rio et al. (Kurfali et al. 2017; Camilleri 2020; AlHadid et al. 2022; Nugroho et al. 2022; Garcia-Rio et al. 2023).

The result of testing H$_5$, the effect of Perceived Trust, shows that confidence measures for e-public services can increase the intention of users to adopt new e-government platforms ($\beta = 0.210$, $p \leq 0.05$). Citizens need to trust that the information available on these platforms is accurate and up to date in order to rely on and use these e-services. When citizens trust these online platforms, they are more likely to actively participate, provide feedback, and engage in various government initiatives, leading to a more interactive and responsive governance model. This outcome aligns with research that identifies this vari-

able as a significant factor influencing attitudes towards e-public services (Papadomichelaki and Mentzas 2012; ElKheshin and Saleeb 2020; AlHadid et al. 2022).

According to the results of testing H$_6$, the impact of Perceived Risk ($\beta = 0.185$, $p < 0.001$), this indicator can increase the adoption of digital administrative services. Internet users tend to be digitally sceptical and cautious about online interactions. Perceived risks, such as concerns about data security and privacy, can influence their willingness to engage with e-government services. During the pandemic, a substantial number of individuals increased their online engagement with e-public services for information access and civic interactions, making them more vulnerable to cyber threats. Despite the common occurrence of cyber threats in online transactions, including phishing and identity theft, such risks exhibit a comparatively lower impact on user attitudes toward e-public services. This phenomenon may be attributed to the adoption of e-identification methods and multi-factor authentication to mitigate safety risks associated with online interactions. This outcome is consistent with the findings presented by Xie et al., Mensah et al., AlHadid et al., and Nugroho et al. (Xie et al. 2017; Mensah et al. 2020; AlHadid et al. 2022; Nugroho et al. 2022).

The result of testing H$_7$, regarding the effect of Service Quality, shows that the quality of e-public services can influence user attitudes towards new e-government systems ($\beta = 0.276$, $p < 0.001$). Positive experiences with e-government services facilitated by high service quality reduce resistance to adopting digital platforms. Users are more willing to transition from traditional to electronic channels when the service quality meets or surpasses their expectations. Additionally, high service quality contributes to positive public perception, which is crucial for the successful implementation and acceptance of e-government initiatives. This result is in line with previous research showing this variable as an important determinant of user attitudes towards adopting and using e-administrative services (AlHadid et al. 2022).

Additionally, our analysis of hypothesis H$_8$ indicates that usage of e-government services is not affected by factors such as gender, place of residence, average income, or educational level. The only factor with a significant effect on customers' perception is their age group.

The determination coefficient R^2 (0.559) (Table 8) shows that approximately 56% of the variability in customer attitudes towards e-public services is explained by the predictor variables (Facilitating Conditions, Perceived Trust, Perceived Risk, and Service Quality). The goodness-of-prediction index Q^2 (0.385) indicates high predictive performance of the model, surpassing the threshold of 0.35 for large predictive relevance.

5.4. Other Models of Customer Attitude towards E-Government Services

To clarify the cause–effect relations between the input and output constructs, we applied the four ML algorithms illustrated in Table 9. Here, the Mean Square Error (MSE) indicates the distance between the evaluated and actual output values of a model, whereas the Mean Absolute Error (MAE) is computed as the average of the absolute differences between the predicted and actual values. Random Forest and AdaBoost outperformed the other ML techniques across all evaluation metrics.

Table 9. Results of using ML algorithms to model user Attitude towards the NRA portal.

ML Method	MSE	MAE	R^2
Decision Tree	0.110	0.175	0.868
SVM	0.096	0.170	0.665
Random Forest	0.056	0.130	0.933
AdaBoost	0.049	0.111	0.941

While the SEM model exhibits a smaller R^2 value compared to traditional machine learning models, its strength lies in the interpretability of its predictions. On the contrary, while conventional ML models showcase higher accuracy (from 0.665 to 0.941), their predictions often lack transparency and are challenging to interpret. Therefore, the choice

between these models depends on the specific priorities of the analysis—whether the decision-maker values a clearer understanding of the underlying relationships (SEM) or prioritizes superior predictive performance (ML).

By leveraging the obtained coefficients from the SEM model, we can apply MCDM methods such as Simple Additive Weighting (SAW) and Weighted Sum Model (WSM). These methods enable the calculation of a composite index, serving as a comprehensive measure for assessing user satisfaction with e-government services.

This study has the following limitations: (1) reliance on data about the new portal of the NRA may limit a comprehensive understanding of the adoption of e-public services, potentially leading to a biased interpretation of the research subject; (2) the sample size and its characteristics may not fully represent diverse demographic perspectives; and (3) the study considered only individual user perceptions, excluding the perspectives of business representatives and public administration officials. These limitations could result in an incomplete depiction of the overall e-government landscape, potentially overlooking some insights and challenges.

6. Conclusions

In recent years, public services have leveraged information technologies to facilitate administrative processes and interactions between citizens, businesses, and government entities. The COVID-19 pandemic accelerated changes in customer habits for online transactions and further strengthened the role of customer satisfaction in the public sector. The transition of public services to the digital space is driven by a variety of factors, including streamlining administrative tasks and improving accessibility for users.

In this study, we collected and utilized a customer dataset to create and validate a set of models that unveil the relationships between consumer perceptions, attitudes, and behaviour towards e-public services. These models can be employed to identify best practices and propose measures for enhancing positive user experiences with digital government services.

The acquired findings can be outlined as follows:

- A primary dataset was collected encompassing users' opinions regarding their use and intention to adopt e-government administrative services. A distribution analysis determined the socioeconomic status of the respondents. A significant portion of respondents (2/3) were below the age of 30, with half of these belonging to Generation Z, and the other half to Millennials. The remaining third consisted of participants with an older age. The majority of participants (96%) resided in urban areas, and 74% were female. In terms of education level, 60% of respondents had completed only high school. Approximately three quarters of respondents (75%) reported using e-government services. Analysis of customer sentiment revealed that the majority of reviews (77%) expressed a non-negative attitude toward e-public services as a convenient tool for e-government interactions. Only a quarter (25%) of the respondents reported that they would recommend the use of e-public services.
- Users of e-government administrative services were classified into two statistically significant clusters. The first "unsatisfied" cluster comprised respondents who reported lower levels of satisfaction in Perceived Ease of Use, Social Influence, Perceived Trust, Perceived Risk, and Service Quality. The second cluster included those with relatively higher levels of satisfaction in Perceived Usefulness and Facilitating Conditions. The minimal distance was observed between user evaluations of Perceived Risk, while the maximal range was detected in Perceived Trust.
- The developed SEM-based model revealed that hypotheses H_4, H_5, H_6, and H_7, which respectively postulated significant impacts on customer attitudes toward e-public services on the part of Facilitating Conditions, Perceived Trust, Perceived Risk, and Service Quality, were verified after a series of predefined checks. Conversely, hypotheses H_1, H_2, and H_3, which respectively suggested that Perceived Usefulness, Perceived Ease of Use, and Social Influence do not affect customer attitude, were

rejected. Our analysis found that customers' usage of e-government services was unaffected by gender, place of residence, average income, or educational level, with only age group showing a significant effect on attitude (H$_8$).

This study creates a theoretical contribution to the understanding of user satisfaction in the context of e-public services by examining the supportive role of various factors in enhancing e-government systems. Emphasizing the significance of these factors, the study highlights their role in overcoming limitations in the delivery of e-public services.

The obtained results have been utilized to generate specific recommendations for stakeholders involved in the digital ecosystem of electronic public services. Regulatory authorities in the domain of public administration can enhance the planning and development of efficient digital service systems. Public organizations can employ the proposed methodology to evaluate, compare, and select alternative approaches for electronic public service delivery. Service providers in the public sector can establish a reliable multi-criteria system for assessing attitudes towards digital administrative services. By understanding the key components that contribute to the perceived value of user satisfaction, IT managers can effectively control and oversee e-government administrative platforms, optimise user experience, and enhance the accountability and transparency of the public sector.

Our plans for future research directions are as follows: (1) increasing the number of respondents in our survey on online public services; (2) comparing our results with similar studies from other countries, with a focus on the usage of e-government services and the moderation effect of different attributes; and (3) exploring the evolution of e-public services after the COVID-19 crisis. Additionally, we aim to conduct further analysis by implementing fuzzy methods to determine the cause-and-effect relationships between factors that impact customer satisfaction in e-public services.

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Informed Consent Statement: Not applicable.

Data Availability Statement: The data stored as csv and pdf files are publicly available at https://data.mendeley.com/datasets/47bp9yhn6j/1 (accessed on 15 January 2024).

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