Technological Forecasting & Social Change 222 (2026) 124398

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

# Examining the factors influencing citizen adoption of e-government chatbot services in Jordan: A longitudinal survey study

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ARTICLE INFO

*Keywords:*
Chatbot
Citizen
Adoption
UTAUT model
E-government adoption
Jordan

ABSTRACT

Many governments are focusing on adopting Artificial Intelligence (AI)-based chatbot technology to enhance work efficiency and improve e-government services. Jordan was among the first Middle Eastern countries to implement AI chatbots to offer various e-services to its citizens. While previous studies have examined the adoption of AI chatbots, they have not explored citizen adoption within the Jordanian context. This research investigates the key factors influencing citizen adoption of e-government chatbot services in Jordan by extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) theory with additional external variables. A longitudinal survey of 319 Jordanian citizens was conducted, with data collected at two different points using Structural equation modeling to test the hypotheses. Results demonstrate that attitude, performance expectancy, effort expectancy, social influence, hedonic motivation, facilitating conditions, self-efficacy, anthropomorphism, personal innovativeness, and trust all positively impacted Jordanian citizens' intentions to use e-government chatbot services, whilst anxiety had a negative effect. Behavioral intentions, facilitating conditions, synchronicity, active control, and ubiquitous connectivity, positively influenced usage behavior, which in turn significantly influenced satisfaction. Satisfaction also influenced citizens' future continuance usage intentions. This study offers valuable insights for enhancing e-government chatbot features to meet citizens' needs within a Middle Eastern context.

## 1. Introduction

Chatbot technology can be defined as an intelligent computer program designed to simulate human conversation with a single user or group of users (Aoki, 2020). AI -based chatbots are integrated with existing knowledge databases and incorporate Natural Language Processing (NLP) to enhance the interaction and efficiency of system access (Alhalabi et al., 2022). Traditionally, chatbot technology has predominantly been incorporated within customer service processes and interactions, requiring simple, somewhat generic answers or offering more detailed specific product information to enhance quality of service (Dwivedi et al., 2023; Lee et al., 2023). Public organizations have transitioned to a more e-government and m-government based infrastructure by adopting chatbots to manage the rapid growth in demand for online digital services and to enhance citizens' interaction. Although some customers may feel somewhat uncomfortable in their interactions with chatbots, the technology is now ubiquitous with numerous use cases that demonstrate widespread adoption (Balakrishnan et al., 2022; Pinochet et al., 2024). The benefits include fast responses to citizens' queries, reducing waiting times, improving service availability, and completing governmental transactions in real time (Mehr et al., 2017). The rapid growth in the development of Chatbot capabilities has facilitated improvements in productivity, efficiency, effectiveness, and accuracy for many public sectors such as health (Zarifis et al., 2021; Zhu

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https://doi.org/10.1016/j.techfore.2025.124398
Received 19 September 2024; Received in revised form 8 October 2025; Accepted 15 October 2025
Available online 23 October 2025

et al., 2022), transportation (Kuberkar and Singhal, 2020), education (Mehr et al., 2017), and social services (Aoki, 2020). Notably, the global market share of chatbot technology was $190.8 million in 2016 and is expected to grow to $1.25 billion by 2025 (Statista, 2023), highlighting that the number of chatbots used by organizations is likely to continue to increase.

Many governments throughout the world (China, Japan, UK) have utilized chatbots to enhance citizens' interaction through the digitalization of services (Aoki, 2020; Ju et al., 2023; Zarifis et al., 2021). Like many countries worldwide, Jordan constantly strives to improve its readiness for AI government services. According to a latest government AI readiness index report issued by Oxford Insights (2024), Jordan has dramatically improved its global e-government ranking as it moved up by 6th places in the government AI readiness index, now standing at 49th out of 188 countries, a notable progress from its 55th rank in 2023. In addition, to continue to keep pace with technological development in e-government services, the Jordanian government has adopted AI chatbot technology for citizens' services.

The government launched its first chatbot in 2018 over Facebook Messenger under the name of "SanadJO". SanadJO means "support" in English (MoDEEJO, 2023). SanadJO provides numerous e-services for particular governmental ministries or organizations, including the Ministry of Health, Greater Amman Municipality, Social Security Corporation, Civil Service Bureau, and Ministry of Industry and Trade. These services focus on three main areas: inquiries, e-payment, and guiding citizens to complete transactions. Lately, the Jordanian government has added four new ministries and organizations to the list of services. The new additional ministries and organizations include Civil Status and Passports, Ministry of Interior, Ministry of Labor, and Ministry of Transportation (MoDEEJO, 2023). The chatbot uses Arabic written text for communication and incorporates active links to provide citizens with easy access information, services, and transaction options directly within the chat interface. The Jordanian government has plans to update its chatbot to include NLP to improve its ability to understand and respond to citizens' inquiries more interactively (MoDEEJO, 2023). In governmental chatbots in Jordan, citizens initiate the conversation by typing "Hello", then the system displays a list of all public organizations that provide services. Citizens would then select an organization name that includes a list of relevant services. Chatbots are available 24/7, and respond to citizens requests in real- time providing personalized assistance. SanadJo uses modern standard Arabic to ensure understanding for all citizens, regardless of their cultural background. However, one limitation of chatbot SanadJo is that it does not support other languages (e.g., English). The government emphasizes that all e-government applications, including chatbots, operate in accordance with legal and ethical standards. A set of security measures, such as authentication mechanisms, ensures citizens' privacy and protects their data when using the system. To increase the level of transparency of AI chatbots in e-government, the government offers comprehensive information about how chatbots work and procedures to protect data (MoDEEJO, 2023). According to Jordan's AI Strategy and Implementation Plan 2023–2027, the government aims to achieve numerous strategic motivators to adopt AI chatbots into citizens' services, including continuous improvement through new technology, enhancing citizen service personalization and to increase the efficiency of the public sector by adopting innovative technologies such as chatbots.

E-government adoption in Jordan is influenced by several key cultural factors. In terms of personal innovativeness, many prior studies found that Jordanian citizens desire to seek out new mechanisms in different types of e-government services in Jordan. For instance, Sawalha et al. (2019) showed that Jordanian citizens had a strong desire to try out Facebook as a new channel for e-government at that time. In Jordan, social influence plays a significant role in shaping technology adoption. As most Jordanians belong to the Arab community, strong family relations are important in their social and cultural life (Abu-Shanab, 2021). Thus, citizens' groups (e.g., friends, relatives, or colleagues) could share and discuss their experiences and ideas regarding e-government applications including chatbots. Furthermore, several studies found the influence of social influences on Jordanian intentions to use e-government applications (Abu-Shanab, 2021; Alarabiat et al., 2021; Alomari, 2021). Jordanian citizens are more likely to accept and use e-government technologies when the social system reinforces their use of them. Furthermore, language preferences could impact chatbot acceptance, as Jordanian citizens may prefer chatbots that support Arabic to enhance usability and understanding. Cultural factors are more closely associated with citizens' perceptions than with the type of technology itself. Thus, these cultural considerations could also influence chatbot adoption in Jordan. Additionally, there are technological infrastructure aspects that could impact chatbot adoption in Jordan including internet accessibility, smartphone penetration, and social media usage. Prior studies discovered that the availability of resources and support (e.g., internet accessibility) would boost Jordanian citizens use of mobile technology within e-government services (Alomari, 2021).

Although Jordan was one of the first countries in the Middle East to integrate AI applications within citizen services, chatbots are a comparatively new technology within e-government services with many citizens being slow to embrace chatbots compared to other technologies (MoDEEJO, 2023). Generally, many governments that have implemented chatbot systems within the context of e-government, have yet to fully understand the complexities of citizens' acceptance and adoption of technology (Chen et al., 2021). The exploration and analysis of citizen adoption of chatbots within the context of public services is still nascent with a number of studies advocating additional research (Aoki, 2020; Zarifis et al., 2021; Zhu et al., 2022). With a greater number of public services being digitized across the developing world, we assert that further empirical research is needed to develop a deeper understanding of the many complexities of increased use and adoption of chatbot technology. Introducing technology without considering citizens' attitudes and behaviors can lead to resistance, limited usage, or low adoption rates. As a result, this may hinder government initiatives aimed at implementing technology. Therefore, academic researchers can assist government understanding of perceptions of technology and provides guidance for managing the complexities of citizen behaviors and their adoption of new technology. Furthermore, regionally focused research in this area has the potential to reveal valuable insights that could greatly inform other governments within the Middle East region, thereby demonstrating real impact to the wider literature. Hence, the main aim of this research is to better understand Jordanian citizens' attitudes and perceptions toward the use and interaction with chatbots and to examine the factors influencing citizen adoption of e-government chatbot services in Jordan. Thus, this paper endeavors to investigate the following questions:

**RQ1**. What factors influence Jordanian citizens' intention to adopt e-government chatbot services?

**RQ2**. How do active control, ubiquitous connectivity, and synchronicity impact usage behavior and satisfaction of e-government chatbot in Jordan?

To achieve the objectives of this study and address the research questions, an adapted model based on the expanded Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model has been developed to explore citizens' acceptance and adoption of e-government chatbots in Jordan. This model is enhanced by comprising a set of external variables (i.e., attitude, trust, anxiety, self-efficacy, personal innovativeness (PI), anthropomorphism, active control (AC), ubiquitous connectivity (UC), and synchronicity).

The remainder of this paper is structured as follows: section 2 provides a review of prior literature pertaining to chatbots in the public sector along with chatbot adoption. Section 3 assesses the theoretical background and hypothesis creation. The research methodology is discussed in Section 4. The results are presented and described in section 5 followed by a discussion of these findings that have emerged from this research in section 6 particularly highlighting the theoretical and practical implications along with the research limitations and suggested future research directions. The paper is concluded in the final section.

## 2. Literature review

The literature on the use of chatbots has seen a surge in interest, with a number of emergent studies published from 2017 onwards. This section will first explore the literature on chatbots use in the public sector, followed by a review of prior studies on citizen chatbot adoption.

### 2.1. Use of chatbots in the public sector

The extant literature highlights that chatbots are one of the most adopted AI technologies within citizens' services (Aoki, 2020; Bharti et al., 2020; Mehr et al., 2017). Chatbots are developed to serve citizens in many ways: answering enquiries, filling out forms, searching for documents, guiding citizens to complete transactions, issuing governmental documents (Aoki, 2020; Mehr et al., 2017) and completing government transactions. Chatbot technology has the capability to automate and support government services to complete daily routine transactions and generally reduce workload, leading to improved levels of service delivery to citizens. This coupled with increased user accessibility to the technology, assists in improving flexibility, transparency and interaction between governments and their citizens (Aoki, 2020). The Government Technology Agency (GovTech) in Singapore uses a Virtual Intelligent Chat Assistant (VICA) platform to powers public-facing chatbots including: Ask Wally to interact with the Public Utilities Board's website, Ask Gayle on the Governments technology website, and Ask Captain Green that allows interaction with the National Environment Agency on environmental and sustainability issues (GoveTech, 2024). VICA operates across more than sixty government agencies, processing over 800,000 citizen queries per month and provides real-time responses (GovTech, 2025).

Some chatbot applications have significant and unique benefits according to the type of service. For instance, Medical Chatbot (Medbot) was implemented during the COVID 19 pandemic to aid citizens' access to health services from cities or rural areas (Bharti et al., 2020). The "Ask Me" chatbot provides timely updates on health guidelines, financial support programs, and travel restrictions (Miller, 2023). Chatbots have also been found to better facilitate access to services, sharing content and improvements to citizen engagement with news organizations (Jones and Jones, 2021).

Modern chatbots depend primarily on Natural Language processing (NLP) (Aoki, 2020) to develop AI techniques that enable computers to understand the natural language of humans (written or spoken) (McCloskey et al., 2024). The integration of NLP into AI chatbots has significantly transformed e-government service delivery. NLP offers numerous benefits in terms of enhancing citizens' and chatbot conversations via voice-enabled features, efficient information retrieval, improving the level of service automation, and personalization (Jiang et al., 2023).

Recent advancements in NLP models such as Large Language Models (LLMs) and Machine Translation Models (MTM) have improved chatbot capabilities in public service context. LLMs are developed and trained to understand, generate, and respond to human language. LLMs have been utilized in the area of citizen interaction by providing answers to citizens' questions (Jiang et al., 2023; Kalyan, 2024). MTM automates the translation of text or speech from one language to another. MTM overcomes language barriers in communication. This ensures that all citizens who speak different languages within the same country can understand information (Boodeea et al., 2025). MTM also enhances the experience of visitors from other countries when they use public services related to tourism, transport, healthcare, and government offices (Boodeea et al., 2025).

### 2.2. Chatbot adoption by citizens

In the last few years, many studies have attempted to investigate the adoption of chatbot technology from a citizen's perspective (e.g., Aoki, 2020; Akkaya and Krcmar, 2019; Cao et al., 2021; Karippur et al., 2020; Kuberkar and Singhal, 2020; Zarifis et al., 2021; Zhu et al., 2022). A summary of these studies is provided in Table 1. Many of these studies have concentrated their research from a particular geographical context. To this end, a number of AI adoption issues were studied in China (Cao et al., 2021; Ju et al., 2023; Li and Wang, 2024; Zhu et al., 2022), UK (Zarifis et al., 2021), Germany (Akkaya and Krcmar, 2019), Japan (Aoki, 2020), India (Kuberkar and Singhal, 2020), and Singapore (Karippur et al., 2020). These studies have focused on citizens' adoption issues of e-government chatbot services. For instance, Aoki (2020) conducted an experimental study by employing an online panel to explore the initial public trust in chatbot-based inquiry services. Kuberkar and Singhal (2020) on the other hand, developed a conceptual model based on a unified theory of acceptance and use of technology (UTAUT) to explore citizens' intention to use AI-chatbot for public transport services in India. They found that Performance Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and anthropomorphism have a significant impact on the intention to use chatbots for public transport services (Kuberkar and Singhal, 2020).

Many previous studies have investigated the effect of emotional factors such as enjoyment (Zhu et al., 2022) or hedonic motivation (Karippur et al., 2020), emotional intelligence (Ju et al., 2023), and satisfaction (Cao et al., 2021). Similarly, numerous existing studies have explored the impact of technological functional factors, including perceived ease of use, and perceived usefulness (Kuberkar and Singhal, 2020; Zarifis et al., 2021), reliability, security, personalization, voice interaction (Zhu et al., 2022), effectiveness, efficiency (Cao et al., 2021). Most prior studies have examined citizens' adoption of chatbots within health public services (e.g., Cao et al., 2021; Zarifis et al., 2021; Zhu et al., 2022). Additionally, some studies have aimed to explore chatbot adoption in different sectors or services, such as public transport services. (Kuberkar and Singhal, 2020) or public engagement (Karippur et al., 2020).

Despite the increasing attention of researchers related to chatbot adoption challenges in public sector, a closer look at e-government chatbot adoption studies reveals a limited number of empirical studies in this area. Most of these empirical studies have tended to concentrate on investigating initial acceptance or citizen intention to use chatbot technologies within public services (e.g., Aoki, 2020; Akkaya and Krcmar, 2019; Cao et al., 2021; Kuberkar and Singhal, 2020). In contrast, few studies have examined AI use behavior (Ju et al., 2023; Li and Wang, 2024). This, in turn, indicates the lack of researcher's focus on investigating usage/use behavior toward AI systems. This matter represents one of the essential research gaps that must be addressed. This research will attempt to fill this gap by examining chatbot citizens' adoption issues (e.g., usage behavior) and long-term adoption issues (e.g., satisfaction and continuous intention). Moreover, the majority of studies have not utilized adoption theories or models to investigate chatbot adoption (Aoki, 2020; Akkaya and Krcmar, 2019; Zarifis et al., 2021) with some existing studies being exploratory in nature and not based on existing theoretical models (Aoki, 2020; Akkaya and Krcmar, 2019). This indicates a theoretical and methodological weakness within the literature. This research will attempt to address this weakness by applying appropriate theoretical constructs to explore citizens' adoption of e-government chatbot services in Jordan. The data presented in Table 1 presents empirical chatbot adoption studies that relate directly to citizen perspectives across a range of government contexts.

The adoption of chatbots in e-government services varies across developing countries, often affected by factors such as technological infrastructure, government policies, cultural considerations, and levels

**Table 1**
Summary of chatbot adoption studies from citizens' perspectives.

| Research Aims | Theory /Model | Internal /External Factors | Sample | Reference |
|---|---|---|---|---|
| Investigated the factors affecting intention to use chatbot-based mobile application for public engagement. | None utilized | - Convenience, collaboration, hedonic motivation, reliability, habit, degree of app savviness, technology benefits, privacy and security. | 268 Public members in Singapore | Karippur et al. (2020) |
| Examined the factors influencing citizens' adoption of chatbots in advice health services. | - Consumer Value Theory (CVT) | - Functional value (personalization, voice interaction), emotional value (enjoyment), epistemic value (learning), conditional value (condition) (Internal factors from CVT) | 371 citizens in China | Zhu et al. (2022) |
| Explored initial public trust. | None utilized | - Purpose and performance factor | 8000 citizens in Japan | Aoki (2020) |
| Identified the initial acceptance. | None utilized | No specified | 1077 citizens in German | Akkaya and Krcmar (2019) |
| Explored the factors affecting citizens' intention to use AI-chatbot for public transport services. | - Unified Theory of Acceptance and Use of Technology (UTAUT) | - PE, EE, SI, and FC (Internal factors from UTAUT). | 463 citizens in India | Kuberkar and Singhal (2020) |
| Investigated the usability affecting intention to use chatbots in patient's guidance services context. | - ISO9241-11: 2018 Standard Framework | - Effectiveness, efficiency, and satisfaction (internal factor) | 346 End users (patients) in China | Cao et al. (2021) |
| Evaluated the impact of trust and personal information privacy concerns on utilizing chatbot in health insurance. | None utilized | - Perceived ease of use and perceived usefulness (From Technology Acceptance Model (TAM) as enablers)<br>-Trust in AI and privacy (external factors as barriers). | 438 participants in UK | Zarifis et al. (2021) |
| Investigated the factors affecting citizens experience of Chinese government chatbot. | - Computers Are Social Actors (CASA)<br>- Stereotype content model (SCM) | - Proactivity, conscientiousness, Manners, Fairness, professionalization, task-oriented language style, warmth perception, competence perception, and citizens experience. | 705 citizens in China | Li and Wang (2024) |
| Explored the effect of social characteristics on citizens' preferences to use government chatbot. | None utilized | - Proactivity, conscientiousness, communicability, emotional intelligence, and identity consistency. | 317 citizens in China | Ju et al. (2023) |

of technology acceptance. In Jordan, although there have been efforts to implement AI chatbots in citizen services, the adoption rate remains moderate. This is largely due to existing limitations in e-government infrastructure, budget constraints, and regulatory obstacles (Alqudah and Muradkhanl, 2021). However, the Jordanian government is working to handle these challenges to ensure the success of AI initiatives and strategies within public services, as outlined in Jordan's AI Strategy and Implementation Plan (2023–2027) (n.d.). In contrast, India has experienced significant growth in AI adoption, particularly in the public service sector. Initiatives like MyGov Helpdesk have enabled India to take advantage of large-scale digital literacy programs and a growing AI ecosystem to enhance the use of chatbots. Unlike Jordan, India's chatbot systems prioritize multilingual support and localized AI models, which make services more accessible to its diverse population (MyGov, 2025). Saudi Arabia, under its Vision 2030 initiative, has heavily invested in AI and digital transformation, integrating chatbots into platforms like Absher to streamline government services. While both Jordan and Saudi Arabia need to understand citizens' behavior toward AI-driven services (Alshabib et al., 2025).

## 3. Theoretical background and hypotheses development

This study utilizes the theoretical model - UTAUT2 as a framework to explain the use of chatbots within Jordanian e-government contexts. The UTAUT2 model is an adaptation of UTAUT, initially presented by Venkatesh et al. (2003). The UTAUT2 model was developed from synopsis of a number of technology adoption theories to form a unified theoretical construct that included a number of new constructs, including: hedonic motivation (HM), price value (PV), and habit (Venkatesh et al., 2012). Chatbots are considered within the umbrella of AI technologies, and a number of AI studies have applied and examined UTAUT models, and most of the results approved its validity to explain the adoption behavior in the AI acceptance domain (Chatterjee and Bhattacharjee, 2020; Gansser and Reich, 2021). Moreover, the UTAUT2 model was initially examined and tested using a participant user base that aligns with the type of participants in this research. Several studies have implemented the UTAUT2 model to explain citizens' intention and behavior toward AI technology across a range of countries (Gansser and Reich, 2021).

Whilst there are strong reasons to utilize the UTAUT2 model to predict citizens' adoption of AI technology, we assert that the model in its current form is insufficient as it ignores the expected role of a number of external variables that influence AI adoption. These include: trust, anxiety, self-efficacy, and other constructs related to the interactivity features of chatbots such as active control, ubiquitous connectivity, and synchronicity. We feel that all these constructs need to be examined in the context of AI adoption for a more predictive and specific model to understand citizens' adoption of chatbots.

The research includes the role of the anthropomorphism construct that focuses on measuring the extent to which nonhuman entity attributes are like human characteristics in terms of social presence and interaction (Sheehan et al., 2020). There is a set of chatbot attributes that can represent human traits such as real-time responses, language-based conversation skills, and politeness via familiar words (Moussawi et al., 2021). These traits could evoke citizen's feelings of anthropomorphism presence during use or interaction with chatbots. Chatbots as new technology, might add a type of ambiguity, which could evoke a citizen's sense of nervousness of losing their information or making errors when using such an application (Li et al., 2021; Pillai and Sivathanu, 2020). Therefore, this research also incorporates the impact of the anxiety factor on citizens' acceptance of chatbots. Furthermore, this research incorporates the set of variables (i.e., ubiquitous connectivity) related to the interactivity aspect between humans and computer software (like chatbot), because chatbots mainly depend on direct interaction, the real-time connection among users and the system, and two-way communication. The existing literature indicated three main constructs that could impact technology interactivity (Lee, 2005; Liu, 2003), namely active control, ubiquitous connectivity, and synchronicity. These factors have been utilized to measure users' adoption of many technologies, such as websites (Liu, 2003) and mobile applications (Alalwan et al., 2020; Lee, 2005). The interactivity aspect of chatbots is not too dissimilar from these technologies. Thus, it could be argued that the interactivity variables might also impact chatbot use. Therefore, this research includes these variables in the conceptual model. This research posits the extension of the UTAUT2 model to include additional variables that can facilitate greater insight to the adoption of chatbot technology in the Jordanian Government context. This research considers the assumptions within the Meta-UTAUT model as set out in Dwivedi et al. (2019) instead of the hypotheses attached to the original UTAUT model (Venkatesh et al., 2003). Therefore, the role of attitude will be considered and its antecedents (PE, EE). Along with enhancing the model's predictive ability, this research further proposes analyzing the role of satisfaction, suggesting that the adoption of chatbots contributes positively to the success of the system (DeLone and McLean, 1992), thereby reinforcing its effectiveness. and continuance intention to use.

As shown in Fig. 1, the primary constructs of the UTAUT2 model (performance expectancy (PE), effort expectancy (EE), social influence (IS), hedonic motivation (HM)) were incorporated into the conceptual research model. Additionally, and in keeping with the Meta-UTAUT model (Dwivedi et al., 2019), the effect of attitude and its antecedents (PE and EE) on BI were included. The research model proposes new external variables and discusses their impact on BI and UB. Finally, satisfaction was considered critical in this model as a key determinant of citizens' intention to continuously use the chatbot.

### 3.1. Hypotheses development

This subsection introduces the major constructs of the conceptual model and develops the proposed hypotheses. Since the roles of Performance Expectancy (H2), Effort Expectancy (H4), Social Influence (H5), Facilitating Conditions (H6), and Hedonic Motivation (H8) in explaining behavioral intention are well established in the base model (UTAUT) and validated in subsequent studies across different technologies (Venkatesh et al., 2012; Dwivedi et al., 2019).

#### 3.1.1. Performance expectancy (PE) → Attitude

PE within the consumer context refers to "the degree to which using a technology will provide benefits to consumers in performing certain activities" Venkatesh et al. (2012, p. 159). Practically, the chatbot provides direct and fast access to government services via live message technology over Facebook or WhatsApp, and accordingly, saving customer's time and effort (Jones and Jones, 2021). Thus, it can ultimately save citizens' time in browsing website pages to find services (Jones and Jones, 2021). Further, chatbots help citizens to get accurate answers to their inquiries and optimize reliability by reducing human errors (Zuiderwijk et al., 2021). Chatbots have been shown to be beneficial and helpful to citizens' daily activities with public organizations, such as inquiries, e-tax payments, and guiding citizens to complete transactions (MoDEEJO, 2023). In Jordan, promotional campaigns are periodically launched that promote the advantages of using AI and its impact on several public sectors generating positive impressions toward chatbots. We argue that perceived usefulness might shape individuals' positive attitudes toward using chatbots. Pitardi and Marriott (2021) asserted the impact of perceived usefulness on attitudes to use AI-based voice assistance in the UK. Abed (2024) also found that PE had a significant effect on citizens' attitude to use government chatbots in Saudi Arabia. Therefore, based on the above discussions, this research proposes the following hypothesis:

**H1**. Performance expectancy will positively influence citizens' attitudes to use chatbots in Jordan.

#### 3.1.2. Performance expectancy → Behavioral intention

Governments highlight the benefits of AI and introduces chatbots as one of the AI technologies (MoDEEJO, 2023). As a result, it could be argued that the PE of the chatbot not only improves citizens' positive attitudes but also contributes to shaping Jordanian citizens' intention toward using such a system. Previous studies also revealed a significant effect of usefulness -or PE- on citizens' intention to use chatbots. Kuberkar and Singhal (2020) found that PE positively affects Indian citizens' behavioral intentions to adopt chatbot applications in public transport services. Based on the data taken from a sample of 677 citizens selected from Indian generation Z, Dogra and Kaushal (2021) confirmed a significant influence of PE on behavioral intentions to use AI-based voice assistants. With this in mind, this research also proposes the following hypothesis:

**H2**. Performance expectancy will positively influence citizens' intentions to use chatbots in Jordan.

#### 3.1.3. Effort expectancy (EE) → Attitude

EE is defined as "the degree of ease associated with consumers' use of technology" (Venkatesh et al., 2012, p. 159). The Jordan government posits chatbot use as a convenient and easy-to-use technology to deliver public services (MoDEEJO, 2023). The perceived EE could increase

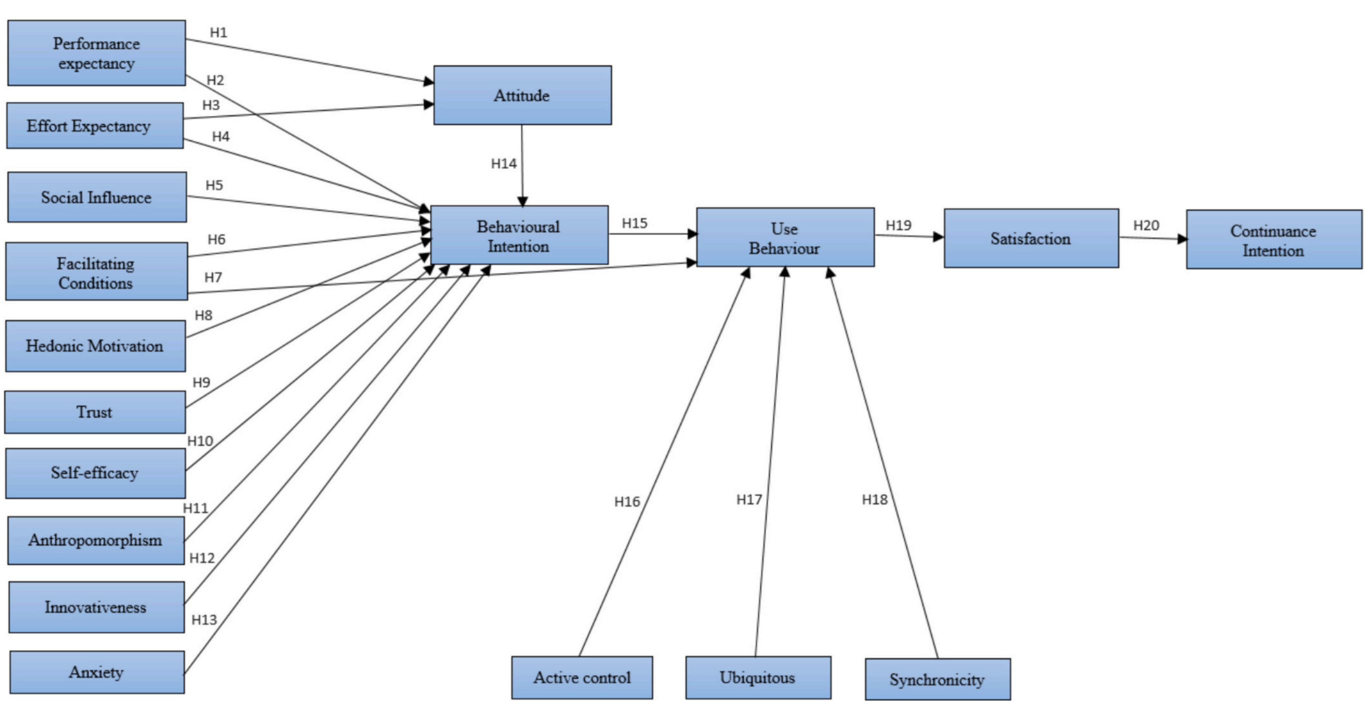


**Fig. 1.** Proposed Research Model (Source: Adapted from DeLone and McLean, 1992; Dwivedi et al., 2019; Venkatesh et al., 2012).

among users as chatbots are very similar to using traditional chat or messaging technology across social networks (Aoki, 2020). Thus, the chatbot's EE might improve citizens' positive attitudes toward using such a system. Many studies have found that EE influences citizens' attitudes to use AI technologies. For instance, Rathnayake et al. (2025) demonstrated that EE positively influenced attitude toward behavioral intention to use chatbots within Sri Lanka's government administration services. Pitardi and Marriott (2021) also confirmed the effect of perceived EE on individuals' attitudes to using chatbots in the UK. Accordingly, the positive citizens' attitude toward chatbots is often increased by perceiving that the system is easy to learn and use. Thus, this research proposes the following hypothesis:

**H3**. Effort expectancy will positively influence citizens' attitudes to use chatbots in Jordan.

*3.1.4. Effort expectancy → Behavioral intention*

In the AI adoption context, the nature of chatbot applications requires a certain level of knowledge, skill, and effort expectancy to use them (Zarifis et al., 2021). Chatbot usage attributes could also affect citizens' readiness to adopt it, as they interact and use the chatbot individually without the employee's intervention (Chen et al., 2021). Moreover, citizens usually attach importance to the system's usability features such as simplicity, understandability, and ease of use (Gansser and Reich, 2021; Zarifis et al., 2021). In addition, several studies proved that EE (or ease of use) plays a crucial role in determining the citizens' intention toward AI technologies. For instance, Kuberkar and Singhal (2020) found the significant impact of effort expectancy on behavioral intentions while analyzing the citizens' intention to use a chatbot in India. Similarly, exploring the Indian adoption of chatbot-based voice assistants, Dogra and Kaushal (2021) found that effort expectancy is one of the most significant predictors of citizens' behavioral intention for using them. Thus, citizens are willing to use the chatbot if they feel it is easy to use. Consequently, this research also proposes the following hypothesis:

**H4**. Effort expectancy will positively influence citizens' intention to use chatbot in Jordan.

*3.1.5. Social influences → Behavioral intention*

According to Venkatesh et al. (2012, p.159), SI is defined as "the extent to which consumers perceive that which is important to significant others in their life (e.g., family and friends) in terms of their belief that they should use a particular technology". In the current research context, governmental chatbots provide public services for all Jordanian citizens. Thus, families, friends and citizens' groups (or work colleagues) often share and discuss their experiences and ideas regarding chatbots' features and benefits privately and on public online forums. As a result, there is a possibility that they affect each other. Furthermore, several studies found the influence of social influences on Jordanian intentions to use e-government applications (Abu-Shanab, 2021; Hujran et al., 2020). Thus, Jordanian citizens are more likely to accept and using e-government technologies when the social system reinforces use them. In the AI adoption domain, many studies also advocate the impact of social influence on AI adoption across different counties (e.g., Gansser and Reich, 2021). Thus, the chatbot is more likely to reach a high level of citizens' acceptance if the social system it is embedded within, supports its use. For these reasons, this research proposes the following hypothesis:

**H5**. Social influences will positively affect citizens' intention to use chatbots in Jordan.

*3.1.6. Facilitating conditions → Behavioral intention*

The construct FC are theorized as "consumers' perceptions of the resources and support available to perform a behavioral change" (Venkatesh et al., 2012, p.159). FC does not only reflect to what extent the individual has knowledge and skills but also to what extent the help has been available from others in using technology. The chatbot would need to be trained on a sufficient level of IT knowledge and skills from citizens (Dogra and Kaushal, 2021). Further, it needs particular types of software because chatbots are embedded within specific applications like WhatsApp or Facebook messenger (Kuberkar and Singhal, 2020). In the context of current research, the chatbot could require a certain level of IT knowledge and skills from citizens (Dogra and Kaushal, 2021; Kuberkar and Singhal, 2020). Further, it needs particular types of software because chatbots are embedded within specific applications like WhatsApp or Facebook messenger (Kuberkar and Singhal, 2020). Many studies demonstrated that the FC construct strongly influences Jordanian citizens' intention and usage of different kinds of e-government systems (Hujran et al., 2020). Overall, the public chatbot working environment is not completely different from other technologies like Facebook and m-government. Consequently, chatbot acceptance is more likely to reach a high level by Jordanian citizens when each usage resources are available. Extant AI adoption studies (e.g., Chatterjee and Bhattacharjee, 2020) has also confirmed the role of the FC or perceived behavioral control to increase citizens' willingness to use AI technologies. Accordingly, it could be argued that the perceived FC of the chatbot impacts citizens' intention to use chatbot in Jordan. Therefore, this research proposes the following hypothesis:

**H6**. Facilitating conditions will positively affect citizens' intention to use chatbots in Jordan.

*3.1.7. Facilitating conditions (FC) → Use behavior*

the nature of chatbot applications requires knowledge, skill, and specific software to use them (Zarifis et al., 2021). Thus, the FC could also influence actual use of chatbots. The availability of necessary software (e.g., Facebook Messenger or WhatsApp) will allow citizens to use and interact with chatbot applications for e-government services in Jordan. Further, the availability of essential chatbot usage skills and experiences will facilitate citizens' chatbot usage for e-government services. Theoretically, the findings from the UTAUT models test (Venkatesh et al., 2003, 2012) found a positive effect of FC on the actual use behavior of technology. Many IS/IT adoption studies have examined this relationship and shown the effect of FC on UB. For example, Hujran et al. (2023)'s findings supported this relationship and asserted that facilitating conditions influence citizens using smart government in the United Arab Emirates (UAE). Katoch and Rana (2023) also confirmed that FC influenced consumers' use of online meets during COVID-19 in India. Thus, FC aspects could positively impact the citizens' use of chatbots which leads to the proposal of the following hypothesis:

**H7**. Facilitating conditions will positively influence citizens' use of chatbots in Jordan.

*3.1.8. Hedonic motivation → Behavioral intention*

According to the UTAUT2 model, HM is conceptualized as "the fun or pleasure derived from using a technology, and it has been shown to play an important role in determining technology acceptance and use" (Venkatesh et al., 2012, p161). The enjoyment factor can be defined as the subjective feelings' citizens experience while using AI chatbots (Zhu et al., 2022). A chatbot (as an emerging IT technology) could improve citizens' perceptions of enjoyment as humans have a curiosity and desire to use any new technology (Pitardi and Marriott, 2021). Citizens also thought that modern technology could add a type of positivity and reduce boredom in previous ways of delivering the public service (Karippur et al., 2020). The chatbot has new features like voice processing and instructions automation facilitating direct interaction between user and system (Zhu et al., 2022). Accordingly, using chatbot might satisfy their curiosity and increase enjoyment as a new e-government tool. The existing studies have measured the role of perceived enjoyment. or HM, in the AI adoption domain. For example, Gansser and Reich (2021) found that HM is one of the drivers behind citizens' intention to accept and use products containing AI technologies in Germany. Karippur et al. (2020) also empirically supported the role of enjoyment in contributing to citizens' willingness to use AI-based mobile applications for Singapore's public engagement. Furthermore, Pitardi and Marriott (2021) proved that the enjoyment factor significantly affects citizens' intention to use chatbot-based voice assistants in the UK. Consequently, this research proposes the following hypothesis:

**H8**. Hedonic motivation will positively influence citizens' intention to use chatbots in Jordan.

#### 3.1.9. Trust (TR) → Behavioral intention

Trust as a concept is associated with the degree of the user's belief that a system or something is good, reliable, or effective (Alalwan et al., 2017). The description of trust has been narrowed according to the e-government studies context. For example, trust in m-government (Liu et al., 2014), e-government websites, or government social media platforms (Alarabiat et al., 2021). Trust in Chatbot (TiC) can be described as the extent to which citizens believe that chatbot features or performance are trustworthy, reliable, and dependable (Nguyen et al., 2021). Within Jordan's e-government services context, the chatbot has many technological features such as accuracy and reliability by reducing human errors (Cao et al., 2021), availability, and accessibility (Coskun-Setirek and Mardikyan, 2017), responsiveness, and real-time connection (Moussawi et al., 2021). These features could develop increased confidence in the eyes of citizens. Zarifis et al. (2021) also found a significant impact of AI trust on citizens' intention to use AI for health insurance services in the UK. Fernandes and Oliveira (2021) showed that trust influences an individual's intention to use chatbots for service encounters. Consequently, TiC could support and increase citizens' willingness to use chatbots for e-government services in Jordan. Accordingly, this research will assume the following hypothesis:

**H9**. Trust in chatbot will positively influence citizens' intention to use chatbots in Jordan.

#### 3.1.10. Self-efficacy (SEL) → Behavioral intention

According to Chao (2019, p.5), self-efficacy is defined as "people's assessments of their effectiveness or ability to perform a specific task well"; it is related to the degree of belief in their ability and skill and how they use them to do a particular job (Hong, 2022). The citizens' self-efficacy beliefs might strengthen from three sources. First, the prior performance for the same tasks with similar applications, as a chatbot is like traditional messaging technology over SMS or social media networks (SMN). Second, the SMN has become familiar to Jordanian citizens, and the chatbot works within its application (MoDEEJO, 2023). Thus, their ability to use SMN platforms (e.g., Facebook and WhatsApp) could generate self-efficacy in using the chatbot. Third, the prior citizen's experiences in completing transactions or gaining public services over other e-government platforms (m-government, websites) might enhance the level of self-efficacy of the chatbot (as it is one of the e-government technologies). These sources could boost their self-efficacy toward chatbot, even if they had never used it before (Chao, 2019; Hong, 2022). The literature on technology adoption demonstrated the supporting role of the self-efficacy construct in shaping individual intention to adopt different kinds of IS. For instance, Brachten et al. (2021) found the indirect effect of self-efficacy on behavioral intention to use a chatbot in the enterprise context. Hong (2022) also found that citizens with AI self-efficacy tend to accept and use AI technology in the US. Accordingly, it can be predicted that citizens with high chatbot self-efficacy are more willing to adopt it. Therefore, this research proposes the following hypothesis:

**H10**. Self-efficacy will positively influence citizens' intention to use chatbots in Jordan.

#### 3.1.11. Anthropomorphism (ATH) → Behavioral intention

According to Sheehan et al. (2020), anthropomorphism is defined as the extent to which a non-human entity's features are like human features. The ATH factor can describe the degree to which citizens sense that conversation or interaction with a chatbot is like a public employee, natural and not artificial (Moussawi et al., 2021). A set of traits attached to a chatbot strengthens this sense. First, the names of chatbot applications are similar to human expressions, are friendly, and familiar to target users. Second, politeness via familiar, respectful words within conversation scenarios (Moussawi et al., 2021). The SanadJo chatbot has employed words familiar with everyday citizens' language and culture - for example, the sentence "Please, let me know how I can help you" (MoDEEJO, 2023). Third, all chatbot applications depend on real-time responses and the chatbot responds simultaneously. This conversation could be like a natural dialogue between citizens and employees (Moussawi et al., 2021). These qualities can generate citizens' perception of anthropomorphism toward chatbot technology. Further, it could affect their intention to use chatbots. In the AI adoption context, Fernandes and Oliveira (2021) also reported that perceived humanness significantly impacts the millennial generation's intention to use AI-powered voice assistants in service encounters. Thus, anthropomorphism has been shown as a factor strongly affecting users' intention to adopt chatbots within the services context (Sheehan et al., 2020) resulting in the following hypothesis being proposed:

**H11**. Anthropomorphism will positively influence citizens' intention to use chatbots in Jordan.

#### 3.1.12. Personal innovativeness (PI) → Behavioral intention

In the technology context the research by Agarwal and Prasad (1998, p.206) defined personal innovativeness as "the willingness of an individual to try out any new information technology". AI-powered chatbots are considered a technological innovation within Jordan's e-government services (MoDEEJO, 2023). The Jordanian government promotes and introduces chatbots as a new and different mechanism to deliver public services or complete transactions (MoDEEJO, 2023). A chatbot is also attached to AI technology, and the people's impression of AI is a technology that provides new solutions to enhance aspects of human ability (Gansser and Reich, 2021). In the AI adoption context, Gansser and Reich (2021) empirically supported the role of personal innovativeness in contributing to German citizens' willingness to use AI technologies in three segments: mobility, household, and health. Hasan et al. (2021) found that individuals strongly wish to experiment with AI-based voice assistants (one of the new high-technology services). Accordingly, it could be argued that citizens are more willing to accept and use chatbots if they perceive that chatbots are a new technology for delivering e-government services. For these reasons, the following hypothesis is proposed:

**H12**. Personal innovativeness will positively influence citizens' intention to use chatbots in Jordan.

#### 3.1.13. Anxiety (ANX) → Behavioral intention

Computer or technology anxiety refers to the degree of a user's apprehension, or even fear, regarding using information system (Rana et al., 2017). The emotions of anxiety among citizens may be evoked from three sources. First, the citizens think they could be losing their information while using the chatbot, as the application asks them to enter personal data (e.g., national number, ID card number). Second, the citizens fear making errors while using chatbot applications, such as the wrong request action on their transactions. Furthermore, chatbots as new technology within e-government services might evoke ambiguity sense toward such a technology (Pillai and Sivathanu, 2020). Thus, these fears could decrease the citizens' motivation to use chatbots. The AI literature predicted that anxiety negatively affects individuals' behavioral intentions to accept chatbot applications. For example, Li et al. (2021) highlights the role of the anxiety factor as one of the hinders that impact Chinese willingness and satisfaction to use chatbot services in the travel sector. Moreover, the role of anxiety was proved by Pillai and Sivathanu (2020) to have a significant negative impact on consumers' intentions to use chatbots for travel planning in India. Accordingly, it could be argued that technological anxiety might influence citizens' intentions to use chatbots and consequently, this research proposes the following hypothesis:

**H13**. Anxiety will negatively influence citizens' intention to use chatbots in Jordan.

*3.1.14. Attitude (ATT) → Behavioral intention*

According to Ajzen (1991), attitude is conceptualized as the degree to which a person has a positive or negative evaluation of a particular behavior. The attitude construct has been considered in many adoption models and theories; TRA, TAM, and DTPB. To further improve the original UTAUT model, Dwivedi et al. (2019) proposed a meta-UTAUT model by including the role of attitude to enhance the model's predictive ability. All the aforementioned models assumed the effect of attitude on behavioral intention. In the context of AI adoption, many prior studies indicated that the attitude construct will positively affect individual behavioral intention. For example, Chatterjee and Bhattacharjee (2020) indicated that the higher level of citizens' positive attitudes toward AI affects their intention to adopt it in the higher education sector. Similar conclusions have been reached by Pitardi and Marriott (2021) concluding a significant association between attitudes and citizens' willingness to use AI-chatbot in the UK. Therefore, based on the above discussions, this research proposes the following hypothesis:

**H14**. Attitude will positively influence citizens' intention to use chatbots in Jordan.

*3.1.15. Behavioral intention (BI) → Use behavior*

The BI as part of the UTAUT2 model is defined as the degree to which the individual tends to use a particular technology (Venkatesh et al., 2012). In the perspective of chatbot adoption, BI can be described as the extent to which citizens are willing to use chatbots for delivering e-government services (Coskun-Setirek and Mardikyan, 2017). It has been found that BI can significantly predict actual usage behavior by several AI studies. For instance, Pillai and Sivathanu (2020) found the significant impact of BI on actual use behavior while analyzing the citizens' adoption of chatbots for travel planning in India. Similarly, exploring the Turkish adoption of chatbot-based mobile applications, Coskun-Setirek and Mardikyan (2017) found that BI is one of the most significant predictors of citizens' use of chatbots. Thus, it could be predicted that the citizens' intention could influence their actual use of the chatbot applications (as a type of e-government technology). Consequently, based on the above discussion, the following hypothesis is proposed:

**H15**. Behavioral intention will positively influence citizens' use of chatbots in Jordan.

*3.1.16. Active control→Use behavior*

According to Liu (2003), AC is defined as “a user's ability to voluntarily participate in and instrumentally influence a communication”, and could be described as the degree of using a chatbot which is manageable by citizens. Chatbot provides citizens with convenient options that enable them to control their interactions (or behavior) with the system (Zhu et al., 2022). For example, voice commands, text chats, or active links. In governmental chatbots in Jordan, the citizens start chatting by typing “Hello”, then the system displays a list of all public organizations that provide services for citizens. At the end of the list, there is an option to exit from the chat, as citizens can leave at any time they desire. If they decide to continue, the citizens can select one from the list by entering its number. After that, the system also presents a list of services, and clients can choose one of them and follow up steps to complete a transaction or process. Most chatbot lists depend on text commands or active links (MoDEEJO, 2023). Thus, the citizen mainly guides conversation scenarios from the first chat into the end. In the context of IS adoption, several studies have demonstrated that the AC construct strongly influences users' acceptance and usage of different kinds of information systems. For example, Zhang et al. (2022) reveal that AC can enhance consumers' use, trust, and continuance intention toward using live streaming e-commerce in China. Alalwan et al. (2020) also discovered that AC (as an interactivity factor) would support consumers' behavioral engagement with mobile shopping. The AC aspects of chatbots might directly support and improve use behavior as citizens sense them during use and interact with systems (Zhang et al., 2022) leading to the following hypothesis being proposed:

**H16**. Active control will directly and positively influence citizens' use of chatbots in Jordan.

*3.1.17. Ubiquitous connectivity → Use behavior*

UC is defined as a system feature that enables users access to information or services system at any time need and regardless of where they are (Lee, 2005). UC can be described as the ability of a system to provide services to citizens from any place at any time (Alalwan et al., 2020). This ability is available basically to governmental chatbots in Jordan, as citizens can use and interact with a chatbot at their convenient time and remotely. Thus, chatbots exceed the time and location constraints attached to using technology like other e-government applications (e.g., websites and m-government) (MoDEEJO, 2023). Furthermore, chatbots work within social networks that are available 24/7, and people can use them from any location. The existing studies found that UC impacts individuals' use of IS. Akram et al. (2019) confirmed that the availability of a tax filing system at all times has effect citizens' use of e-tax services in Pakistan. Although the effect of UC on use behavior has not been examined yet in the e-government chatbot services context. The UC characteristic of chatbots is like other technologies such as websites and Mobile. Accordingly, it can be predicted that the ubiquitous connectivity of chatbots might motivate citizens to use such technology. Further, it could increase their use of public e-government services. As such, this research formulated the following hypothesis:

**H17**. Ubiquitous connectivity will directly and positively influence citizens' use behavior of chatbots in Jordan.

*3.1.18. Synchronicity → Use behavior*

Synchronicity can be conceptualized as the characteristic that enables technology to complete individuals' requests in real-time, immediately or without delay (Liu, 2003; Zhang et al., 2022). In the context of current research, the chatbot already supports a live connection feature as citizens use or request services, and the system responds immediately (Zhang et al., 2022). Further, the chatbot depends mainly on direct dialogues among citizens and the system. Thus, all parties are available and interact at the same time (Liu, 2003). The synchronicity feature boosts the chatbot's ability to act like public employees in the citizens' services context through real-time interaction (Li et al., 2021). Consequently, citizens might increase using chatbots due to the synchronicity benefit as it ensures present service quickly and on time. Prior studies indicated that perceived synchronicity is essential in determining an individual's behavior toward IS acceptance and use (i.e. Zhang et al., 2022; Lu et al., 2019). Zhang et al. (2022) demonstrated that synchronicity is one of the drivers behind citizens' behavior in interacting with live streaming commerce applications in China. This has been further highlighted by Orden-Mejía and Huertas (2021) who revealed that when a chatbots' ability is able to provide services promptly, then this has a supported impact on consumers' adoption and satisfaction with chatbots for the tourism sector. Accordingly, it could be argued that citizens might sense that chatbots can supply timely answers to their inquiries or requests leading to the following hypothesis being put forward:

**H18**. Synchronicity will directly and positively influence citizens' use of chatbots in Jordan.

*3.1.19. Use behavior (UB) → satisfaction*

UB as part of the UTAUT models is defined as the degree to which individuals use or interact with technology in a particular context (Venkatesh et al., 2012). UB can be described as the extent to which citizens use chatbots to request e-government services (Gansser and Reich, 2021). In the Jordan context SanadJO has been utilized to request public services or inquiries. The Ministry of Digital Economy and Entrepreneurship (MoDEEJO, 2023) confirmed that the actual number of e-transactions is about 2.8 billion across Jordan's e-government platforms during 2022. The chatbot is one of the e-government platforms in Jordan. Thus, it can be predicted that citizens' chatbot usage is relatively high in Jordan. Chatbots have many features that improve its performance in aspects of effectiveness and productivity. For example, accuracy, reliability, accessibility, anthropomorphism, and responsiveness (Li et al., 2021). Consequently, the feelings of satisfaction among citizens may increase because using the chatbot and sensing its performance meets their needs in delivering public services. Cheng and Jiang (2020) found a strong relationship between consumers' perceived chatbot attributes (e.g., social presence, enjoyment) and satisfaction via the use of a commercial chatbot in the USA. Abed (2024) also demonstrated that UB significantly affects citizen intentions to continue using government chatbots in Saudi Arabia. Thus, it can be suggested that citizens' chatbot use and frequency of usage could be an indicator to predict satisfaction. Therefore, this research proposes the following hypothesis:

**H19**. Use behavior will positively influence citizens' satisfaction with chatbots in Jordan.

*3.1.20. Satisfaction (SAT) → Continuance intention*

Satisfaction is defined as the degree to which individuals believe that the available technology meets their needs (Li et al., 2021). Almost all the emotional satisfaction results from using or interacting directly with information systems that fit users' requirements in a particular context (DeLone and McLean, 1992). In fact, satisfaction has been shown to play an essential role in explaining technology use (Bhattacherjee, 2001), success (DeLone and McLean, 1992), and acceptance (Venkatesh et al., 2012).

Citizens perceive that chatbot quality might enhance satisfaction. As a result, satisfaction could positively affect their future behavioral intention toward the chatbot system. In this respect, Nguyen et al. (2021) confirmed that satisfactory experiences with chatbot use increase the user's willingness to repeat the same use behavior with the system in the future. Cheng and Jiang (2020) also empirically showed that satisfaction is one of the most significant predictors of continued intentions to use chatbot services in the US. Citizens could frequently use chatbots when they have satisfactory experiences with them. Thus, this research proposes the following hypothesis:

**H20**. Satisfaction will positively influence citizens' continuance intention to use chatbots in Jordan.

## 4. Methodology

This research aims to investigate the influence factors have on two key issues: namely citizens' intention and use behavior. It is crucial to explore the adoption process fully by tracking the same users over time toward e-government chatbots for several reasons. It allows us to thoroughly measure citizens' intentions first and identify the main factors that impact their intention (PE et al.) and then investigate usage behavior with affected factors (active control et al.). Furthermore, it enables us to examine post-adoption behavior issues (i.e., satisfaction, continuance intention). Theoretically, human intention and behavior cannot be measured simultaneously toward a specific activity (Venkatesh et al., 2012). In the IS field, users think and format their intentions to use the system at a specific time, then generate a willingness to accept or use it (Jeyaraj et al., 2023). Thus, the users' willingness has been generated to use the system in a specific period and their actual use behavior in a future period of time. Logically, the intention is first and then "use behavior" (Jeyaraj et al., 2023; Venkatesh et al., 2012). Consequently, this research required data collection in two stages at two different longitudinal time points from the same respondents. Thus, a longitudinal approach was taken as it was deemed to be the most appropriate for this study. Following the guidance from Maier et al. (2023), the researchers initially distributed and collected the first (intention survey) questionnaire. After four months, the researcher distributed and collected the second questionnaire (behavior use survey) from the same respondents. The UTAUT2 model has been tested using a two-stage data collection approach. Venkatesh et al. (2012) collected data from non-adopters in the first stage to explore customer intentions, while in the second stage, they collected data from adopters to examine usage behavior. Furthermore, many technology adoption studies have applied a longitudinal approach to investigate two or more adoption-related issues at different time points using the same respondents (Laradi et al., 2024; Mou et al., 2017).

The measurements for all constructs have been identified and developed based on the prior IS adoption literature. As illustrated in Table 2 (Appendix A), eighteen constructs are given, along with their coding, items and reference sources. It should be noted that the type of questions have been formulated based on existing studies, for example, the constructs PE, EE, SI, FC, HM, BI, and use behavior, questions, were adopted from Venkatesh et al. (2012).

This research conducted two tests to validate the questionnaire data: pre-test and pilot test as recommended by existing IS adoption studies (e.g., Venkatesh et al., 2003, 2012). For the pre-test phase, the surveys were shared with a panel of IT experts. This panel consisted of ten individuals from academia and industry within Jordan. Experts were selected based on their prior experience in digital transformation and public services in Jordan. They include AI/IT researchers, managers of e-government services, and IT professionals with expertise in developing, implementing, or evaluating AI-based government services. The two questionnaires were then subsequently updated based on the experts feedback. Pilot tests were then conducted with 30 Jordanian citizens with the respondents confirming that questions were simple, straightforward, readable, and understandable in both questionnaires. Thus, no further updates on the questionnaire versions were required.

In order to further validate survey questions, this research conducted Cronbach's alpha tests to measure the degree of consistency between different items of each construct (Bhattacherjee, 2012). Nunnally (1978) demonstrated that Cronbach's alpha value exceeding 0.70 indicates the adequate reliability level of the internal consistency reliability of the construct. Many IS/IT adoption studies (Alalwan et al., 2017; Viswanath et al., 2012) depend on this value as an indicator of consistency reliability level for their constructs. Accordingly, this research conducted Cronbach's alpha tests on items for each construct in both questionnaires. Analysis of Cronbach's alpha values for each construct demonstrated that all constructs presented a satisfactory reliability level because each group of items for each construct achieved a value of 0.70 or above.

The target population for this study was Jordanian citizens, and there are restrictions or attributes to ensure the proper choice of a sample of the whole population. First, the respondents must hold Jordanian nationality since many e-government chatbot services have been introduce for Jordanian citizens only. For example, inquiries about competitive ranking in the civil service bureau or government support for citizens in energy consumption. Second, the minimum age of participants is 18 years old. This aligns with the age-related access to e-government services in Jordan and also follows ethical principles for this research. The surveys were subsequently distributed to citizens from four main cities in Jordan: Amman, Zarqa, Irbid, and AL-Mafraq. The choice to collect data from these cities was to ensure a representative and diverse sample of the Jordanian population was captured due to their dense population (Statistics Division of Jordan, 2023). These cities were selected to gather a comprehensive snapshot of societal trends and behaviors toward e-government chatbot services in Jordan. Moreover, being the largest cities in Jordan, they are hubs where people have computers and internet access (Statistics Division of Jordan, 2023). The substantial populations in these cities imply a higher likelihood of widespread internet access for utilizing e-government services, making them ideal settings for investigating the prevalence and impact of such services. Two methods to distribute questionnaires were applied: (1) physically distributing a paper survey in person or by post, (2) electronically distributing the survey via email, or social media (Bhattacherjee, 2012). The survey was distributed to citizens in person or by post to avoid bias against specific participants due to a lack of internet access since some citizens might not use the internet or social media during the data collection period.

In the first stage, 550 surveys were distributed on 15th July 2022 to citizens living in four cities in Jordan. 45 were paper-based, and the remainder were electronic copies. By 15th August 2022, 334 were returned fully completed from electronic distribution. In addition, 25 paper surveys were received from manual distribution; three were incomplete since the respondents only answered 25 % or below of the total survey questions. Furthermore, these respondents did not provide contact information for the second data collection stage. Therefore, their responses have been excluded (Sekaran and Bougie, 2016). Accordingly, the valid responses for the first stage were 356 from both types of distributions, and the response rate was 64.72 %. By January 2, 2023, 356 participants (the valid responses) were contacted to complete the second survey that aimed to explore use behavior. In total, 356 were distributed. By the end of March 2023, 319 were received fully completed (representing valid responses for further analysis). Overall, the response rate was 89.60 % completed.

At the end of the first survey, we asked participants to provide a communication method, either an email address or a postal code (for paper-based surveys). A unique code (anonymous code) was generated for each participant and attached to the provided email address or postal code for contact purposes only. This code can be used to link data across the two stages without directly identifying the participant's personal information (e.g., name, job, etc.). Thus, we ensure the privacy of participants and anonymity, aligning with ethical principles in longitudinal surveys, as recommended by many scholars (e.g., Audette et al., 2020; Lessof, 2009; Yurek et al., 2008). In the second stage, emails were sent to all participants in one message, rather than sending individual emails. Reminder emails were also sent based on this approach. For those who provided a postal code, the paper survey was delivered via postal mail.

To confirm the collected data's reliability, Common Method Bias (CMB) was used (Bhattacherjee, 2012). CMB represents the degree of unauthentic common variance between exogenous and endogenous variables measured simultaneously. As part of this process, researchers conducted Harman's single factor analysis using SPSS to test the CMB. According to Podsakoff et al. (2003), a cumulative variance extracted value below 50 % indicates that the CMB does not influence the data. For this study the CMB test revealed that the cumulative variance extracted was 25.84 %. Thus, the current dataset was deemed free from the CMB. An independent samples *t*-test was conducted using SPSS to compare the mean scores of respondents who completed the questionnaire on paper versus those who completed it online. The results showed no statistically significant difference between the two groups, $t(317) = 0.147$, $p = 0.654$. The mean score for the paper group was 5.41 (SD = 0.052), while the online group had a mean score of 5.44 (SD = 0.088), resulting in a mean difference of 0.03. The study also followed the approach recommended by Armstrong and Overton (1977) to address the related issues of non-response bias. The main findings, in this respect, showed that there were no significant differences between respondents who completed the questionnaire earlier or later.

The data was further scrutinized using several tests (i.e., outlier's analysis and normality) at the preliminary stage to ensure cleanliness and appropriateness of the data to further analysis. Outlier value analysis via Mahalanobis-D squared distance (D2) revealed 18 outlier cases have a *p*-value of 0.000 or less within the dataset. Noteworthy, any *p* value equal to or less than 0.000 is an outlier case using the D2 test (Hair Jr. et al., 2006). Removing outliers' cases could improve the multivariate analysis but may negatively impact the results' generalizability (Hair Jr. et al., 2006). A small number of outliers is not problematic since the number of valid responses is large (Hair Jr. et al., 2006). Thus, the decision was taken to keep these outliers in the dataset. In order to ensure that the data received was normally distributed, it was essential to conduct statistical analysis to determine the normality aspect of the dataset (Byrne, 2010; Kline, 2015). As a result, the analysis using SPSS showed all the values given within the normality distribution. As all skewness values were less than the cut-off point of 3. Furthermore, all Kurtosis values did not exceed the recommended cut-off of 7 (Kline, 2005).

Structural Equation Modeling (SEM) was used to validate the current conceptual model and to test the proposed hypotheses. The SEM analysis was undertaken through a two-step method: measurement model and the structural model in line with Kline (2015).

## 5. Results

### *5.1. Respondents' profile and characteristics*

Demographic data was collected in alignment with a longitudinal approach from the same sample population through two surveys that were conducted at different stages. The participants' answers to demographic and technology usage variables are the same in both surveys. As demonstrated in Table 3, the gender data shows that the sample was balanced with 55.8 % male and 44.2 % female participants. The age data demonstrate that most participants were between the ages of 31 and 40 (41.1 %). The majority of respondents (44.8 %) held a bachelor's degree. The distribution of income indicates that a large percentage of

**Table 3**
Demographic characteristics of the chatbot adoption survey.

| Item | Demographic Profile | Number of Respondents ($N = 319$) | Percentage (%) |
|---|---|---|---|
| Gender | Male | 178 | 55.8 % |
| | Female | 141 | 44.2 % |
| Age | 18–24 | 38 | 11.9 % |
| | 25–30 | 56 | 17.6 % |
| | 31–40 | 131 | 41.1 % |
| | 41–50 | 81 | 25.4 % |
| | 51–60 | 9 | 2.8 % |
| | 60+ | 4 | 1.3 % |
| Education level | High school | 45 | 14.1 % |
| | Diploma | 17 | 5.3 % |
| | Bachelor | 143 | 44.8 % |
| | Master | 62 | 19.4 % |
| | PhD | 27 | 8.5 % |
| | Other | 25 | 7.8 % |
| Monthly Income Level (JOD) | No income | 2 | 0.60 % |
| | Less than 400 | 33 | 10.30 % |
| | 400–600 | 93 | 29.20 % |
| | 601–800 | 69 | 21.60 % |
| | 801–1000 | 61 | 19.10 % |
| | 1001–1200 | 38 | 11.90 % |
| | 12,001–1500 | 17 | 5.30 % |
| | 1500+ | 6 | 1.90 % |
| Internet usage for e-government services | Never | 0 | 0 |
| | Less than one year | 64 | 20 % |
| | 1–2 years | 57 | 17 % |
| | 2–3 years | 34 | 10.7 % |
| | More than 3 years | 164 | 52.1 % |

respondents (29.20 %) had a monthly income between 400 and 600 JOD. The results highlighted that around half of the participants (52.1 %) reported using the internet for e-government services for more than 3 years, whereas 10.7 % of respondents have been using it for 2 to 3 years.

The second data collection stage data analysis demonstrates that all participants declared they had experience with chatbots for e-governments services (see Table 4). The data showed that most respondents (75.9 %) have chatbot experience of more than one month to two months. Furthermore, the highest percentage of participants (31 %) stated that they use chatbots occasionally.

The used behavior (UB) construct has also been investigated by a seven-point Likert scale, the anchors range from '"never' to 'several times a day'. The UB was measured through this method by Venkatesh et al. (2012) because UB attached to the frequency of citizens" use of e-government chatbot services. As demonstrated in Table 5, the results for all measurement items related to use behavior showed mean values close to or above 5, with the exceptions of UB2 (4.39) and UB5 (4.40). In contrast, all items measuring satisfaction reported mean values greater than 5, indicating a high level of satisfaction among citizens with e-government chatbots.

### 5.2. Structural equation model (SEM) analysis

This research incorporates SEM to analyze complex data structures and relationships. AMOS software was used to conduct statistical measurements and structural model stages.

#### 5.2.1. Measurement model: Confirmatory factor analysis (CFA)

This stage involves two steps: testing model fitness in the CFA and assessing the reliability and validity of the constructs.

*5.2.1.1. Model fitness.* The estimation of model goodness of fit was calculated through the following indices: CMIN/DF, GFI, AGFI, NFI, CFI, and RMSEA (Hair et al., 2012). As shown in Table 6, the initial measurement fit indices found that CMIN/DF, GFI, NFI, CFI, and RMSEA reached target values. However, AGFI does not reach an acceptable value. Thus, the model does not fit the data adequately. Accordingly, it is essential to apply a number of criteria to enhance the model's fitness (Hair et al., 2012). The fit model indices were enhanced by inspecting factor loading values (also known as standardized regression weight (SRW)). It was found that some items were under the cut-off value of 0.50 (Hair et al., 2012), which included two items (UB2, UB5) from the use behavior construct, two items (SEL6, SEL7) from the self-efficacy construct, one item (FC4) from facilitating conditions construct, one item (AC1) from the active control construct, and one item (ATH2) from the anthropomorphism construct. Therefore, in alignment with Byrne (2010) and Hair et al. (2012), the decision was made to remove these items from further analysis. Moreover, the modification indices introduced improved suggestions regarding covariation. Accordingly, the error terms of SAT1 and SAT2; CI3 and CI4; UC1 and UC2; SYN1 and SYN2; and SEL1 and SEL2 were all correlated (Hooper et al., 2008). After doing so, all model fit indices were found to exceed the expected level of values in final estimates, as shown in Table 6.

**Table 4**
Demographic characteristics of chatbot usage for e-government services.

| Item | Demographic Profile | Number of Respondents (N = 319) | Percentage (%) |
|---|---|---|---|
| Length of time using chatbots to access e-government services. | Never | 0 | 0 |
| | Less than one week | 0 | 0 |
| | 1–2 weeks | 3 | 9 % |
| | 2–3 weeks | 45 | 14.1 % |
| | More than 1–2 months | 242 | 75.9 % |
| | More than 2–3 months | 29 | 9.1 % |
| | More than 3 months | 0 | 0 |
| Frequency of use of chatbots for e-government services. | Never | 0 | 0 |
| | Very Rarely (Once a month) | 22 | 6.8 % |
| | Rarely (Several times a month) | 55 | 17.2 % |
| | Occasionally (About once a week) | 102 | 31.9 % |
| | Often (Several times a week) | 73 | 23.2 % |
| | Very often (About once a day) | 54 | 16.9 % |
| | Always (several times a day) | 16 | 5.01 % |

**Table 5**
Descriptive statistics measurement items (satisfaction and usage behavior).

| Constructs | Items | Mean |
|---|---|---|
| Satisfaction | SAT1 | 5.81 |
| | SAT2 | 5.82 |
| | SAT3 | 5.87 |
| | SAT4 | 5.89 |
| Use behavior | UB1 | 5.65 |
| | UB2 | 4.39 |
| | UB3 | 5.50 |
| | UB4 | 5.59 |
| | UB5 | 4.40 |
| | UB6 | 5.66 |

*5.2.1.2. Constructs reliability and validity.* The statistical findings indicated that all items (latent constructs) have factor-loading values ranging from 0.58 (CI3) to 0.95 (SYN3); thus, they were all above the threshold value of 0.50 (Hair et al., 2012). They were also statistically significant with $p$-values less than 0.0001. In addition, all reliability and validity indicators for constructs are within the recommended values. As shown in Table 7, Cronbach's alpha (CA) values exceeded the cut-off point of 0.70 (Nunnally, 1978). Similarly, statistical findings indicated that the constructs have a composite reliability (CR) value above the cut-off point of 0.70 (Hair et al., 2012). Moreover, the average variance extracted (AVE) value of the constructs ranged from 0.53 (use behavior) to 0.76 (performance expectancy), which all are above the target level of 0.50, as recommended by (Fornell and Larcker, 1981). As per Table 8, all inter-correlation coefficients between latent constructs were below the suggested value of $\pm 0.90$ (Kline, 2015). Furthermore, the square root of the AVE values for all latent constructs was higher than the inter-correlation values accounted for by the corresponding constructs (Fornell and Larcker, 1981).

#### 5.2.2. Structural model

The structural model must be assessed before testing the hypotheses (or path coefficients) among independent and dependent variables. As shown in Table 9, the statistical analysis found that the structural model had acceptable goodness of fit to data. Accordingly, the structural model is validated for further analysis.

The analysis findings demonstrated that all 20 hypotheses in the conceptual model were supported. As presented in Table 10, all had a $p$-value below the cut-off point of 0.05, and the value of the critical ratio is above the recommended value of $\pm 1.96$. The results confirmed that performance expectancy ($\gamma = 0.571, p = 0.000$) and effort expectancy ($\gamma = 0.234$, $p = 0.007$) were both significant predictors of citizens' attitudes. Behavioral intention was found to be significantly predicted by performance expectancy ($\gamma = 0.144, p = 0.041$), effort expectancy ($\gamma = 0.125, p = 0.046$), attitude ($\gamma = 0.119, p = 0.021$), social influences ($\gamma = 0.083, p = 0.037$), facilitating conditions ($\gamma = 0.092, p = 0.048$), hedonic motivation ($\gamma = 0.102, p = 0.046$), self-efficacy ($\gamma = 0.084, p = 0.045$),

**Table 6**
Model fit indices of the measurement model of chatbot adoption.

| | χ2 | DF | $p$ | χ2/DF < 3.00 | AGFI ≥ 0.80 | CFI ≥ 0.90 | PNFI > 0.50 | RMSEA ≤ 0.06 |
|---|---|---|---|---|---|---|---|---|
| Initial estimates | 4292.86 | 2696 | 0.000 | 1.592 | 0.759 | 0.904 | 0.718 | 0.043 |
| Final estimates | 3059.53 | 2187 | 0.000 | 1.399 | 0.819 | 0.944 | 0.753 | 0.035 |

Note: $\chi^2$ = Chi-Square; DF=Degrees of Freedom; $p$ = Significance; AGFI = Adjusted Goodness of Fit Index; CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; PNFI=Parsimonious Normed Fit Index.

**Table 7**
Results of reliability and validity.

| | CA | CR | AVE |
|---|---|---|---|
| SYN | 0.89 | 0.88 | 0.669 |
| PE | 0.90 | 0.90 | 0.763 |
| EE | 0.91 | 0.91 | 0.728 |
| SI | 0.87 | 0.87 | 0.693 |
| FC | 0.83 | 0.82 | 0.616 |
| HM | 0.87 | 0.87 | 0.691 |
| ATH | 0.83 | 0.83 | 0.621 |
| SEL | 0.88 | 0.87 | 0.587 |
| CI | 0.85 | 0.85 | 0.540 |
| SAT | 0.92 | 0.91 | 0.741 |
| UB | 0.82 | 0.82 | 0.539 |
| BI | 0.87 | 0.87 | 0.708 |
| TR | 0.91 | 0.91 | 0.638 |
| ATT | 0.90 | 0.90 | 0.659 |
| PI | 0.88 | 0.88 | 0.711 |
| ANX | 0.93 | 0.92 | 0.756 |
| UC | 0.88 | 0.87 | 0.647 |
| AC | 0.85 | 0.85 | 0.600 |

anthropomorphism (γ = 0.070, $p$ = 0.028), personal innovativeness (γ = 0.061, $p$ = 0.044), anxiety (γ = −0.033, $p$ = 0.029), and trust (γ = 0.093, $p$ = 0.033). Citizens' use behavior was also noticed to be significantly predicted by behavioral intention (γ = 0.155, $p$ = 0.040), facilitating conditions (γ = 0.154, $p$ = 0.038), active control (γ = 0.276, $p$ = 0.003), ubiquitous computing (γ = 0.190, $p$ = 0.023), and synchronicity (γ = 0.227, $p$ = 0.003). Moreover, citizen's use behavior (γ = 0.124, $p$ = 0.009) significantly influenced their satisfaction with the chatbot. Finally, satisfaction (γ = 0.837, $p$ = 0.000) also significantly impacts citizens' intention to continuously use chatbots for e-government services.

To address potential concerns about multicollinearity between the independent and dependent variables in testing the current conceptual model, we analyzed the variance inflation factor (VIF) for all the paths in the model. According to Brace et al. (2003) and Diamantopoulos and Siguaw (2000), multicollinearity is flagged if the VIF value exceeds 10. As shown in Table 10, the resulting VIF values were found to range from 1.014 to 3.049, which is well below the threshold value (10).

Fig. 2 represents the results of structural model test that includes relationships among dependent and independent variables within the model, and the $R^2$ values extracted in the endogenous construct were as follows: 66 % for attitude, 86 % for behavioral intention.

Path coefficient analyses was also conducted for both gender (male and female) to see if there any differences in the causal paths between independent and dependent factors. As seen in Table 11, ATT was significantly predicted by PE for both male and female; yet, the path coefficient value accounted for this relationship was stronger for females (γ = 0.755, $p$ < 0.001). Likewise, the role of EE in predicting ATT was more considerable for females (γ = 0.096, $p$ = 0.353) in comparison with males. As for the role of ATT on BI, ATT considerably impacts BI (γ = 0.281, $p$ = 0.009), but for males, this impact was not significant (γ = 0.081, $p$ = 0.268). Similarly, EE does not significantly impact BI in either gender, though the effect is slightly stronger for females (β = 0.163, $p$ = 0.1) than for males (β = 0.099, $p$ = 0.396). PE has a significant impact on BI for males (γ = 0.219, $p$ = 0.045), but this relationship is not significant for females (γ = 0.149, $p$ = 0.407).

While male respondents' intention was strongly predicted by HM (γ = 0.209, $p$ = 0.008), this impact was not significant for females' ones (γ = 0.014, $p$ = 0.894). TR has a minor influence on BI for females (γ = 0.173, $p$ = 0.087) but is not significant for males (γ = 0.080, $p$ = 0.269). Likewise, ATH significantly predicts BI for males (γ = 0.167, $p$ = 0.008), while for females, this effect is negligible (γ = 0.010, $p$ = 0.909).

Interestingly, ANX negatively impacts BI in both genders, but the impact is significant only for females (γ = −0.109, $p$ = 0.044), while it is non-significant for males (γ = −0.046, $p$ = 0.287). Other variables, (i.e. PI, SEL, and SI), do not exhibit significant effects on BI for either gender, though SI shows a marginal significance for males (γ = 0.131, $p$ = 0.042).

Regarding UB, FC considerably influence UB for females (γ = 0.293, $p$ = 0.019) but not for males (γ = 0.088, $p$ = 0.403). Both SYN and AC significantly predict UB for males (SYN: γ = 0.208, $p$ = 0.018; AC: γ = 0.219, $p$ = 0.015), while these relationships are weaker for females (SYN: γ = 0.163, $p$ = 0.082; AC: γ = 0.166, $p$ = 0.104). Furthermore, UC significantly influences UB for females (γ = 0.232, $p$ = 0.023) but not for males (γ = 0.115, $p$ = 0.176).

A striking difference is found in the relationship between BI and UB. While BI significantly predicts UB for males (γ = 0.287, $p$ = 0.006), it is non-significant for females (γ = −0.021, $p$ = 0.865). Finally, UB significantly predicts SAT for females (γ = 0.195, $p$ = 0.044) but not for males (β γ = 0.120, $p$ = 0.154). Ultimately, SAT strongly predicts CI for both males (γ = 0.536, $p$ < 0.001) and females (γ = 0.718, p < 0.001).

The structural model was also tested for the factors predicting BI and ATT. As seen in Table 12, BI was significantly predicted by ATT (γ = 0.154, $p$ = 0.021); PE (γ = 0.150, $p$ = 0.034); EE(γ = 0.120, $p$ = 0.045); HM (γ = 0.102, $p$ = 0.046); TR (γ = 0.093, $p$ = 0.033); ANH (γ = 0.070, $p$ = 0.029); PI (γ = 0.062, $p$ = 0.042); SEL (γ = 0.083, $p$ = 0.049); SI (γ = 0.083, $p$ = 0.040); ANX (γ = −0.033, $p$ = 0.028); and FC (γ = 0.154, $p$ = 0.038). A good portion of variance was accounted in BI with R2 value of 86 % and ATT with R2 value of 66 %.

A structural Model test was also conducted for the factors that only predicted actual use behavior. As can be seen in Table 13, all factors were approved to have a significant impact on the actual use behavior. AC was the most significant factor predicting UB (γ = 0.202, $p$ = 0.003) followed by SYN (γ = 0.193, p = 0.003); and then FC (γ = 0.184, $p$ = 0.021). UC was also approved to have a significant impact on UB (γ = 0.153, $p$ = 0.019). UB, in turn, significantly predicts SAT (γ = 0.116, $p$ = 0.009). Finally, a strong and significant relationship was approved between SAT and CI (γ = 0.632, $p$ = 0.000). It is also worth mentioning that these factors were able to account for about 39 % of variance in UB. About 33 % of variance accounted for SAT and 40 % of variance in CI.

## 6. Discussion

This study provides comprehensive insights into the determinants of citizens' adoption and use of AI-powered chatbot services in the Jordanian e-government context. Several key findings stand out. First, performance expectancy (PE) exerted the strongest influence on citizens' attitudes (γ = 0.571), underscoring that perceived usefulness remains a central driver of positive evaluations of chatbot services. This result is broadly consistent with prior studies in the UK and Germany (Pitardi and Marriott, 2021; Gansser and Reich, 2021), yet our findings extend this knowledge to the e-government domain where efficiency gains and

**Table 8**
Factor correlation matrix.

| | SYN | PE | EE | SI | FC | HM | ATH | SEL | CI | SAT | UB | BI | TR | ATT | PI | ANX | UC | AC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SYN | 0.818 | | | | | | | | | | | | | | | | | |
| PE | 0.047 | 0.873 | | | | | | | | | | | | | | | | |
| EE | 0.009 | 0.817 | 0.853 | | | | | | | | | | | | | | | |
| SI | 0.106 | 0.603 | 0.616 | 0.833 | | | | | | | | | | | | | | |
| FC | −0.054 | 0.580 | 0.581 | 0.363 | 0.785 | | | | | | | | | | | | | |
| HM | 0.009 | 0.719 | 0.692 | 0.639 | 0.469 | 0.831 | | | | | | | | | | | | |
| ATH | −0.055 | 0.455 | 0.478 | 0.454 | 0.250 | 0.510 | 0.788 | | | | | | | | | | | |
| SEL | −0.005 | 0.621 | 0.564 | 0.617 | 0.398 | 0.561 | 0.503 | 0.766 | | | | | | | | | | |
| CI | 0.065 | 0.403 | 0.421 | 0.372 | 0.331 | 0.419 | 0.284 | 0.539 | 0.735 | | | | | | | | | |
| SAT | −0.068 | 0.091 | 0.068 | 0.007 | 0.115 | 0.117 | 0.139 | 0.181 | 0.628 | 0.861 | | | | | | | | |
| UB | 0.296 | 0.318 | 0.278 | 0.319 | 0.309 | 0.296 | 0.181 | 0.239 | 0.275 | 0.155 | 0.734 | | | | | | | |
| BI | 0.007 | 0.824 | 0.809 | 0.690 | 0.603 | 0.758 | 0.602 | 0.703 | 0.490 | 0.157 | 0.337 | 0.841 | | | | | | |
| TR | −0.014 | 0.610 | 0.599 | 0.532 | 0.490 | 0.593 | 0.638 | 0.608 | 0.390 | 0.082 | 0.279 | 0.733 | 0.799 | | | | | |
| ATT | 0.055 | 0.779 | 0.721 | 0.569 | 0.587 | 0.682 | 0.524 | 0.632 | 0.444 | 0.162 | 0.301 | 0.800 | 0.633 | 0.812 | | | | |
| PI | 0.149 | 0.100 | 0.146 | 0.144 | 0.124 | 0.126 | 0.104 | 0.169 | 0.231 | 0.066 | 0.103 | 0.221 | 0.147 | 0.129 | 0.843 | | | |
| ANX | −0.045 | −0.196 | −0.258 | −0.099 | −0.118 | −0.104 | 0.007 | −0.083 | −0.123 | 0.003 | −0.010 | −0.236 | −0.155 | −0.145 | −0.117 | 0.870 | | |
| UC | 0.211 | 0.376 | 0.300 | 0.296 | 0.178 | 0.403 | 0.143 | 0.343 | 0.300 | 0.029 | 0.319 | 0.353 | 0.321 | 0.339 | 0.134 | −0.012 | 0.804 | |
| AC | 0.380 | 0.021 | 0.023 | 0.083 | 0.120 | 0.100 | −0.030 | 0.057 | 0.101 | 0.053 | 0.345 | 0.117 | 0.082 | 0.098 | 0.205 | −0.049 | 0.200 | 0.775 |

**Table 9**
Model fit indices of the structural model of chatbot adoption.

| $X^2$ | DF | *P* | $X^2$/DF $< 3.00$ | AGFI $\geq 0.80$ | CFI $\geq$ 0.90 | PNFI $> 0.50$ | RMSEA $\leq 0.06$ |
|---|---|---|---|---|---|---|---|
| 3255.184 | 2242 | 0.000 | 1.452 | 0.823 | 0.935 | 0.762 | 0.038 |

**Table 10**
Hypotheses testing.

| No | Hypothesized path | Standardized estimate | Critical Ratio | *p*-value | VIF |
|---|---|---|---|---|---|
| H1 | PE → ATT | 0.571 | 7.067 | *** | 2.804 |
| H2 | PE → BI | 0.144 | 2.047 | 0.041 | 3.049 |
| H3 | EE → ATT | 0.234 | 2.694 | 0.007 | 2.471 |
| H4 | EE → BI | 0.125 | 1.997 | 0.046 | 2.780 |
| H5 | SI → BI | 0.083 | 2.083 | 0.037 | 1.147 |
| H6 | FC → BI | 0.092 | 1.976 | 0.048 | 1.543 |
| H7 | FC → UB | 0.154 | 2.074 | 0.038 | 1.371 |
| H8 | HM → BI | 0.102 | 1.994 | 0.046 | 2.149 |
| H9 | TR → BI | 0.093 | 2.135 | 0.033 | 2.084 |
| H10 | SEL → BI | 0.084 | 2.005 | 0.045 | 1.865 |
| H11 | ATH → BI | 0.070 | 2.2 | 0.028 | 1.656 |
| H12 | PI → BI | 0.061 | 2.017 | 0.044 | 1.069 |
| H13 | ANX → BI | −0.033 | −2.183 | 0.029 | 1.100 |
| H14 | ATT → BI | 0.119 | 2.303 | 0.021 | 2.620 |
| H15 | BI→ UB | 0.155 | 2.05 | 0.040 | 1.682 |
| H16 | AC → UB | 0.276 | 3.023 | 0.003 | 1.203 |
| H17 | UC → UB | 0.190 | 2.27 | 0.023 | 1.180 |
| H18 | SYN → UB | 0.227 | 2.954 | 0.003 | 1.206 |
| H19 | UB → SAT | 0.124 | 2.618 | 0.009 | 1.014 |
| H20 | SAT → CI | 0.837 | 10.055 | *** | 1.073 |

service quality improvements appear particularly salient to citizens. The findings highlighted how effort expectancy (EE) significantly influenced both attitudes and behavioral intention. While this aligns with earlier research on AI adoption (Balakrishnan et al., 2022; Chatterjee and Bhattacharjee, 2020), our results contrast with Tian et al. (2024), who found no such effect in the Chinese higher education context. This divergence highlights how context matters: in e-government services, ease of use is especially critical for encouraging adoption among diverse citizen groups, many of whom may have limited digital literacy. The constructs - social influence (SI) and facilitating conditions (FC) emerged as important drivers of intention and use behavior. While some prior studies reported insignificant effects of these factors in Saudi Arabia and China (Abed, 2024; Tian et al., 2024), our findings confirm their significance in the e-government context, suggesting that institutional trust, peer influence, and the provision of adequate technical support are vital for sustaining chatbot usage. Importantly, we also observed a significant relationship between FC and actual use behavior, a relationship that has been underexplored in prior AI adoption research.

The results highlight the relevance of additional individual-level factors. Hedonic motivation (HM), trust, self-efficacy, anthropomorphism, and personal innovativeness, all positively shaped behavioral intention, while technology-related anxiety exerted a negative influence. Notably, the negative effect of anxiety on intention to use e-government chatbots represents a novel contribution, as this relationship has been scarcely investigated in the chatbot adoption literature. By demonstrating that anxiety undermines citizens' willingness to engage with chatbots, our study adds an important psychological dimension to the UTAUT2 model in the public sector. Consistent with prior UTAUT-based research (Dwivedi et al., 2019; Tamilmani et al., 2021), we found strong evidence that behavioral intention translates into use behavior, and that usage behavior, in turn, enhances satisfaction and continuance intention. Among these, the path from satisfaction to continuance intention was the strongest (γ = 0.837), highlighting satisfaction as the most decisive factor in ensuring ongoing engagement. This contrasts with UTAUT2 findings in other domains, where PE often

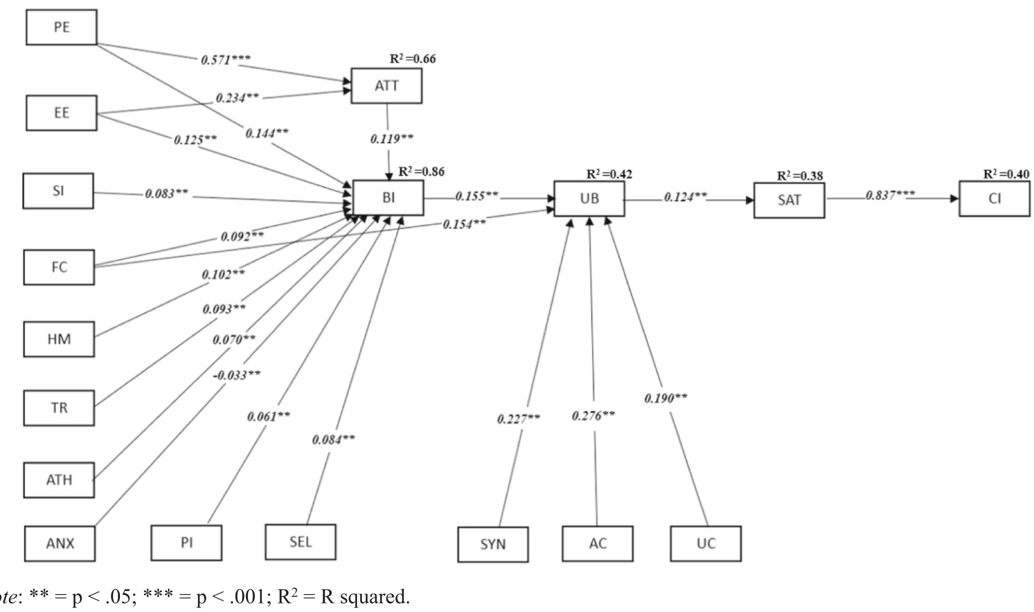


**Fig. 2.** Structural model results. *Note*: ** = $p < 0.05$; *** = $p < 0.001$; $R^2$ = R squared.

**Table 11**
Comparison of path coefficients between male and female groups.

| Path | Estimate (Male) | P-value (Male) | Estimate (Female) | P-value (Female) |
|---|---|---|---|---|
| ATT < — PE | 0.430 | 0.001 | 0.755 | *** |
| ATT < — EE | 0.096 | 0.353 | 0.400 | 0.002 |
| BI <— ATT | 0.081 | 0.268 | 0.281 | 0.009 |
| BI <— EE | 0.099 | 0.396 | 0.163 | 0.1 |
| BI <— PE | 0.219 | 0.045 | 0.149 | 0.407 |
| BI <— HM | 0.209 | 0.008 | 0.014 | 0.894 |
| BI <— TR | 0.080 | 0.269 | 0.173 | 0.087 |
| BI <— ATH | 0.167 | 0.008 | 0.010 | 0.909 |
| BI <— ANX | −0.046 | 0.287 | −0.109 | 0.044 |
| BI <— PI | 0.054 | 0.222 | 0.045 | 0.407 |
| BI <— SEL | 0.073 | 0.299 | 0.092 | 0.258 |
| BI <— SI | 0.131 | 0.042 | 0.120 | 0.178 |
| BI <— FC | 0.096 | 0.1 | 0.109 | 0.173 |
| UB < — FC | 0.088 | 0.403 | 0.293 | 0.019 |
| UB < — SYN | 0.208 | 0.018 | 0.163 | 0.082 |
| UB < — AC | 0.219 | 0.015 | 0.166 | 0.104 |
| UB < — UC | 0.115 | 0.176 | 0.232 | 0.023 |
| UB < — BI | 0.287 | 0.006 | −0.021 | 0.865 |
| SAT < — UB | 0.120 | 0.154 | 0.195 | 0.044 |
| CI < — SAT | 0.536 | *** | 0.718 | *** |

exerts the strongest effect.

Taken together, these findings advance the literature in several ways. They demonstrate that while many determinants of chatbot adoption are consistent with established UTAUT2 relationships, contextual differences (e.g., between public services and education or commercial domains) produce important variations, such as the role of effort expectancy, social influence, and facilitating conditions. They also contribute novel evidence regarding the negative role of anxiety and the underexplored link between facilitating conditions and actual use behavior in e-government services. More broadly, the study offers one of the most comprehensive examinations of chatbot adoption in the public sector to date, integrating technological, psychological, and contextual factors into a unified framework.

**Table 12**
Structural model test of BI factors.

| Path | Estimate | C.R. | P-value |
|---|---|---|---|
| ATT < — PE | 0.567 | 7.028 | *** |
| ATT < — EE | 0.238 | 2.730 | 0.006 |
| BI <— ATT | 0.120 | 2.305 | 0.021 |
| BI <— EE | 0.126 | 2.002 | 0.045 |
| BI <— PE | 0.150 | 2.120 | 0.034 |
| BI <— HM | 0.102 | 1.994 | 0.046 |
| BI <— TR | 0.093 | 2.131 | 0.033 |
| BI <— ATH | 0.070 | 2.180 | 0.029 |
| BI <— ANX | −0.033 | −2.203 | 0.028 |
| BI <— PI | 0.062 | 2.037 | 0.042 |
| BI <— SEL | 0.083 | 1.968 | 0.049 |
| BI <— SI | 0.083 | 2.058 | 0.040 |
| BI <— FC | 0.154 | 2.074 | 0.038 |

**Table 13**
Structural model test for factors predicting UB, SAT, and CI.

| Path | Estimate | C.R. | P-value (Female) |
|---|---|---|---|
| UB < — FC | 0.184 | 2.310 | 0.021 |
| UB < — SYN | 0.193 | 3.001 | 0.003 |
| UB < — AC | 0.202 | 3.006 | 0.003 |
| UB < — UC | 0.153 | 2.338 | 0.019 |
| SAT < — UB | 0.166 | 2.616 | 0.009 |
| CI < — SAT | 0.632 | 10.055 | *** |

### 6.1. *Theoretical contribution*

Several theoretical contributions have arisen from this study in the context of the knowledge of IS, AI, and chatbot adoption literature. First, this study found the effect of these internal variables on citizens' intention and their use behavior. Thus, the findings of this study present additional evidence and validation for UTAUT models. Furthermore, it has included the role of use behavior on citizens' satisfaction as part of the IS success model (DeLone and McLean, 1992). The results of this study found the effect of UB on satisfaction and confirmed the IS success model assumption in this aspect. Hence, this study also provides a theoretical contribution to the DeLone and McLean (1992) model. Secondly, the review of the literature on chatbot adoption indicates that the majority of studies have focused on initial acceptance or citizen intention to use chatbot technology in e-government services (Aoki, 2020; Cao et al., 2021; Kuberkar and Singhal, 2020). Few studies have examined issues related to UB chatbots in an e-government context (Ju et al., 2023; Li and Wang, 2024). Thus, this study is a step further in contributing to the existing chatbot literature by exploring crucial constructs related to citizens' behavior after the initial adoption stage namely - use behavior, satisfaction, and continuing intention.

As this study has included many external variables (e.g., anthropomorphism, active control, ubiquitous computing), besides UTAUT's internal variables (PE et al.), this has offered further contribution to the field. Most noteworthy is the fact that it was found that external variables have an impact on behavioral intention and use behavior. Thus, providing additional evidence to predict citizens' intentions and use behavior toward chatbots in e-government services in Jordan. Moreover, based on the $R^2$ test results, the data highlights that the predictive power of the present model in BI is greater than both UTAUT and UTAUT 2 models (Venkatesh et al., 2003, 2012). Furthermore, extending the UTAUT2 model with new external variables has provided a new theoretical contribution to the UTAUT literature. Lastly, prior studies have been conducted across different geographical contexts. However, to our knowledge none of these studies has been conducted within the Jordan public context. This study represents the first comprehensive examination of chatbot adoption within the public sector in Jordan, and more broadly, in Arab countries. Cultural, social factors and conditions affect citizens' perceptions, opinions, or beliefs toward information systems (Zarifis et al., 2021) with the Arab countries having their own particular cultural norms. Such norms and values vary across countries and regions, influencing perceptions and behaviors of chatbot adoption (Chen et al., 2021; Dogra and Kaushal, 2021). The level of digital literacy in societies significantly influences their acceptance of technology, as well as public trust or anxiety toward new technologies like chatbots (Aoki, 2020). Additionally, some cultures may be more open to adopting new technologies, while others may resist change. It is the aim of this study to explore this in the Jordanian context. Moreover, the degree of connection among people and the influence of citizens on each other vary between countries and cultures (Dogra and Kaushal, 2021; Kuberkar and Singhal, 2020). Many researchers highlighted that the results of AI adoption studies could be different when studies are conducted in other locations since citizens' perceptions and perspectives may change over time or place (Aoki, 2020; Chen et al., 2021; Zarifis et al., 2021). Thus, the results of existing studies conducted in China and India are unlikely to be generalizable to other countries (e.g., Jordan). These matters represent one of the essential gaps this study addressed by investigating chatbot adoption issues in the Jordanian context. The findings also affirm the validity of extended UTAUT models in the context of e-government chatbot services adoption in Jordan.

### 6.2. *Implications for practice and policy*

This study's findings indicate that the Jordanian government should adopt a set of practices to increase citizens' adoption of e-government chatbot services. As the chatbot is a comparatively new technology in the Jordanian e-government services, many citizens are unaware what resources are required to use it or how to access these services. Thus, consideration needs to be given to applying special promotional campaigns about chatbot benefits across public channels (e.g., TV, Newspapers, social media). The Jordanian government could use these campaigns to clarify IT resources (e.g., Facebook Messenger or WhatsApp) that citizens need to use their chatbot platforms (MoDEEJO, 2023). These campaigns will also need to inform potential users by highlighting that chatbots require software similar to traditional messaging technology across social networks. By doing this, non-adopters could be interested in trying chatbots since all essential software and hardware could be easily available to them. Further, these promotional campaigns should clarify that using chatbots is very similar to phone messaging (e.g., SMS) and chat technology currently being used across social networks (Aoki, 2020). Traditional chat or messaging technology has been widely used and spread among Jordanian citizens (MoDEEJO, 2023). As Jordanian citizens already have experience using traditional messaging technologies, promotional awareness could support citizens' belief in their ability to use e-government chatbots. The government should also adopt plans to continuously innovate chatbots in the e-government services sector, highlighting any new services and features incorporated into their services for the benefit of their citizens. The government should encourage citizens to use chatbots to complete government transactions electronically rather than visiting public agencies in person. Increasing the use of chatbots can assist reduce energy consumption and the need for transportation, thereby mitigating their negative impact on the environment and climate. Besides, relying more on digital documents can help reduce recycling issues associated with paper usage. These procedures support the UN's SDG 13: Climate Action, which aims to safeguard the environment.

Public service managers could also use these campaigns to provide clear and concise information about how to use chatbots effectively, with mindful security measures, and ethical data protection policies. These campaigns should explain data usage and storage practices, whilst assuring citizens that their data is protected, and that the chatbot adheres to data privacy regulations. The IT teams should also regularly test and maintain the current chatbot security features to specify and fix any issues that may provoke user apprehension. Furthermore, they should regularly update the chatbot security characteristics to stay ahead of possible risks. By incorporating these practices into the implementation of chatbots, Jordan can enhance sustainability, aligning with the UN's SDG 16, which aims to ensure transparency and ethical AI use. These practices could minimize citizens' anxiety and make them more willing to use e-government chatbot services. Government decision makers could consider collaborating and engaging with local social media influencers or opinion leaders with a strong following in the Jordanian context. Influencers or leaders can promote chatbots, share their positive experiences, and influence (and inform) their followers by encouraging and empowering them to use such technology. Additionally, the government should coordinate with local businesses or organizations that have influence and expertise in demonstrating chatbots value in e-governments services and the community. The government could then showcase positive feedback and reviews from chatbot adopters in e-government services and use well known and trusted platforms among its citizens to display this feedback and reviews.

IT teams embedded within e-government teams need to continuously improve chatbot features to reinforce positive citizens' perception, intention, and use of e-government chatbot services to foster trust by its citizens. IT management should make e-government chatbot services available on multiple platforms, such as government websites, mobile applications, and social media networks, to meet citizens where they are most comfortable. Indeed, these practices add flexibility regarding time and place for chatbot usage. Citizens are more likely to increase their use and adoption of chatbots when they feel that e-Government services can be accessed anytime and anywhere. Developers need to be mindful of continuously adding new human friendly attributes to chatbot functionality to increase adoption. For example, voice interaction language features to make the chatbots more friendly and relatable for citizens. The successful implementation of these anthropomorphism aspects in the context of chatbots can enhance citizens' intention to use such technology in e-government services. Furthermore, the IT team should incorporate more interactive features into the current chatbot to support users with disabilities, such as implementing a voice-enabled feature for visually impaired people. These practices will ensure inclusivity and accessibility of e-government chatbot service for all Jordanian citizens. Furthermore, they will support the UN's Sustainable Development Goals

(SDGs). Particularly, SDG 10: Reduced Inequalities.

IT teams should employ modern standard Arabic in the current chatbots to ensure it is widely understood across various Arabic-speaking citizens. Avoid regional dialects like Jordanian Colloquial Arabic to maintain neutrality. Furthermore, provide an option for English, since many Jordanians are fluent in both languages. These practices could ensure flexibility interaction to a broader audience and create a culturally appropriate, respectful for the Inclusive of all citizens' groups in Jordan. Developers could also use more conversational language and greetings to welcome interaction with citizens. This could be achieved through the use of polite and friendly/welcoming language along with expressions of gratitude to chatbot conversations. Thus, effective use of empowering language in chatbot responses by inserting words encouraging users to take action confidently and adding in more flexible options to chatbot conversations, will foster positive user experiences. For example, options that enable citizens to pause the conversation and continue it later. Incorporating such active control features will improve citizens' ability to control the conversation flow and decide how (and when) they want to proceed with the chatbot interaction. Moreover, ensuring the chatbot continuously performs efficiently and promptly to citizen queries is essential whilst minimizing loading times and delays to complete users' requests. The delivery of quick and efficient e-government chatbot services can support citizens' use of the technology, leading to greater user satisfaction in the e-government services context. Many factors influence adoption, such as social influence, trust, and personal innovation, all of which are closely tied to cultural habits. The recommended practices for the Jordanian government can be also valuable for other Arab countries that share similar cultural and digital behaviors, such as UAE, Saudi Arabia, Egypt, and Morocco. Furthermore, as Arabic is a common language across these countries, chatbot language-related guidelines are particularly important for the governments of Arab countries to ensure the usefulness and usability of e-government chatbot services.

### *6.3. Limitations and future research direction*

In this research, the data was collected from four cities in Jordan over a specified period. Thus, the results could be different since citizens' perceptions and perspectives may change over time or place. Therefore, future studies could consider other cities in Jordan. Furthermore, cultural norms and values vary across countries. Thus, the results of this research are applicable to the Jordan context and may not be suitable for all countries. Therefore, future studies could explore citizens' adoption of chatbot services in different geographical contexts. This research collected data from non-adopters in the first stage to examine the role of many variables (e.g., PE, EE, SI, FC, HM). Noteworthy, the present research selected this way of data collection based on the method of Venkatesh et al. (2012) in validating UTAUT2. However, it is essential to acknowledge that there is a need to further investigate these variables by collecting data from adopters of chatbots since citizens' perceptions may change after using e-government chatbot services. To address this limitation, future studies could collect data from adopters of chatbots to reassess the impact of these variables and to present more accurate findings. In addition, this research focused on the public sector (especially e-government services). The results may not be generalized to all sectors because each sector has unique features that may influence citizens' adoption of chatbots. Therefore, future studies could consider the private sector (e.g., the banking sector). Although the present research has attempted to present an exhaustive understanding of citizens' adoption of e-government chatbots, its conceptual model was limited to five external variables to examine behavioral intention and three external variables to explain usage behavior. To address this limitation, future studies can expand the current conceptual model with other external variables (e.g., perceived helpfulness, perceived risk, responsiveness, and personalization). The research has also omitted the role of moderators in the relationship between independent and dependent variables. Future studies could examine how various moderators (e.g., digital literacy or cultural characteristics) affect citizens' attitudes, intentions, and behavior toward e-government chatbot services in Jordan. This research did not examine potential mediating effects among constructs, such as behavioral intention mediating the relationship between facilitation conditions and usage behavior. Future studies could investigate these mediating effects to enhance understanding of the dynamics between these constructs.

## 7. Conclusions

To our knowledge this is the first research to explore factors affecting citizen adoption of e-government chatbot services in Jordan. This research proposed a centric chatbot adoption model based on and extending UTAUT2. We conducted a two-stage survey to explore chatbot adoption within Jordanian government services. This study goes beyond mere intention to actual usage behavior and further investigates post-adoption outcomes, including user satisfaction and the intention for continuous usage, hence offering a comprehensive knowledge of the chatbot adoption process. The study advances IS/AI/chatbot adoption theory by demonstrating that both UTAUT internal variables and selected external factors (anthropomorphism, active control, ubiquitous computing) shape citizens' behavioral intention (BI) and that use behavior (UB), shapes citizen BI and UB in e-government chatbots. A key contextual contribution is the first comprehensive examination in Jordan (and the wider Arab public sector), addressing how cultural norms, social influence, and digital literacy impact adoption.

The findings highlight the importance of improving technological aspects (e.g., anthropomorphism) that shape citizen's intention to use e-government chatbots. The results also indicate the importance of addressing anxiety related technology concerns by demonstrating how they negatively impact citizens' willingness to use chatbots in e-government services. Furthermore, the results highlight the importance of technological features, such as active control, ubiquitous connectivity, and synchronicity, in supporting the usage behavior of chatbots in citizen services. Thus, this research adds valuable and practical empirical findings to the existing literature in the e-government field.

Chatbots are a comparatively new technology within e-government citizens' services in Jordan. To boost adoption of e-government chatbots, it is recommended that the government should run broad public-channel campaigns that clarify access and benefits, pair them with transparent security/privacy practices and continuous inclusive feature improvements. Additionally, it is recommended that these improvements include: multi-platform availability, voice/assistive and human-friendly design. We also recommend leveraging trusted influencers and promote digital transactions that reduce impacts on the environment, thereby advancing SDGs 13, 16 and 10. The current findings will thus be of use to decision makers within the Jordanian government to better understand citizen adoption and to improve chatbot features and interaction to meet citizens' needs based on the evidence encapsulated in this study. This study underscores the necessity of addressing both technological design and psychological readiness in fostering citizens' adoption of chatbot government services. Accordingly, policymakers and developers are encouraged to adopt a dual strategy that not only advances technological design but also enables users' psychological readiness, such as building trust, reinforcing self-efficacy, and promoting personal innovativeness.

## CRediT authorship contribution statement

**Ibrahim Mohamad:** Writing – original draft, Conceptualization, Methodology, Data curation. **Laurie Hughes:** Writing – review & editing, Supervision, Conceptualization, Methodology. **Ali Abdallah Alalwan:** Writing – review & editing, Methodology. **Tegwen Malik:** Writing – review & editing, Supervision. **Yogesh K. Dwivedi:** Writing – review & editing, Supervision, Conceptualization, Methodology.

## Appendix A. Constructs and measurement items

**Table 2**
Constructs and measurement items.

| Constructs | Code | Items | Sources |
|---|---|---|---|
| Performance Expectancy | PE1 | I would find chatbots for e-government services useful in my daily life. | Venkatesh et al. (2012) |
| | PE2 | Using chatbots would help me to accomplish e-government services or transactions more quickly. | |
| | PE3 | Using chatbots would increase my productivity in completing e-government services or transactions. | |
| Effort Expectancy | EE1 | Learning how to use the chatbot would be easy for me. | Venkatesh et al. (2012) |
| | EE2 | My interaction with the chatbot would be clear and understandable. | |
| | EE3 | I would find the chatbot easy to use. | |
| | EE4 | It is easy for me to become skillful at using the chatbot for e-government services. | |
| Social Influences | SI1 | People who are important to me think that I should use the chatbot (as a new e-government technology). | Venkatesh et al. (2012) |
| | SI2 | People who influence my behavior think that I should use the chatbot for e-government services. | |
| | SI3 | People whose opinions that I value prefer that I use the chatbot for e-government services. | |
| Facilitating Conditions | FC1 | I have the resources necessary to use the chatbot (e.g., mobile and WhatsApp). | Venkatesh et al. (2012) |
| | FC2 | I have the knowledge necessary to use the chatbot for e-government services. | |
| | FC3 | The chatbot is compatible with other technologies I use (e.g., SMS, Facebook chat, or WhatsApp). | |
| | FC4 | I can get help from others when I have difficulties in using chatbots. | |
| Hedonic Motivation | HM1 | Using the chatbot would be fun. | Venkatesh et al. (2012) |
| | HM2 | Using the chatbot would be enjoyable. | |
| | HM3 | Using the chatbot would be very entertaining. | |
| Behavioral Intention | BI1 | I intend to use the chatbot for e-government services in the future. | Venkatesh et al. (2012) |
| | BI2 | I will always try to use chatbots in my daily life. | |
| | BI3 | I plan to use chatbots in the future. | |
| Attitude | ATT1 | Using the chatbot to access e-government services would be a good idea. | Balakrishnan and Dwivedi (2021) |
| | ATT2 | Using the chatbot to access e-government services would be a wise idea. | |
| | ATT3 | I like the idea of using the chatbot for e-government services. | |
| | ATT4 | Using the chatbot to access e-government services would be pleasant. | |
| | ATT5 | Overall, my attitude toward chatbots is favorable. | |
| Self-Efficacy | SEL 1 | I can use the chatbot for e-government even if there was no one around to tell me what to do. | Compeau and Higgins (1995) |
| | SEL 2 | I can use the chatbot for e-government services even if I have only the guidelines for using it. | |
| | SEL 3 | I can use the chatbot for e-government services if I have seen someone else using it before trying it myself. | |
| | SEL 4 | I can use the chatbot for e-government services if I can call someone for help when I get stuck. | |
| | SEL 5 | I can use the chatbot for e-government services if someone else helps me in getting started. | |
| | SEL 6 | I can use the chatbot for e-government services if I have a lot of time to do that. | |
| | SEL 7 | I can use the chatbot for e-government services if someone shows me how to do it first. | |
| Anthropomorphism | ATH1 | I believe interaction with a chatbot for e-government services would be similar to interaction with a public employee. | Balakrishnan et al. (2022); Balakrishnan and Dwivedi (2021) |
| | ATH2 | I believe interactions with the chatbot for e-government services would be natural. | |
| | ATH3 | I believe interactions with the chatbot for e-government services would be interactive. | |
| | ATH4 | I believe conversation with the chatbot should not be artificial. | |
| Personal Innovativeness | PI1 | If I heard about new information technology, I would look for ways to experiment with it. | Gansser and Reich (2021); Hasan et al. (2021) |
| | PI2 | I like to try new and different technologies. | |
| | PI3 | Among my peers, I would be usually one of the first people who try new technologies. | |
| Anxiety | ANX1 | Using technology such as chatbots for completing e-government transactions makes me anxious. | Rana et al. (2017). |
| | ANX2 | I might hesitate to use chatbot services for fear of making mistakes I cannot correct. | |
| | ANX3 | It scares me to think that I could lose a lot of information when using chatbots for completing e-government transactions by hitting the wrong option. | |
| | ANX4 | Using the chatbot is somewhat scary to me. | |
| Trust | TR1 | I believe that chatbot is trustworthy. | Alalwan et al. (2017) |
| | TR2 | I do not doubt the honesty of the chatbot. | |
| | TR3 | I feel assured that legal and technological structures adequately protect me from problems with the chatbot. | |
| | TR4 | Even if not monitored, I would trust the chatbot to do the job right. | |
| | TR5 | The chatbot has the ability to fulfil its task. | |
| | TR6 | Overall, I trust the chatbot. | |
| Active Control | AC1 | I have a great deal of full freedom over my using experience in the chatbot. | Alalwan et al. (2020); Lee (2005) |
| | AC2 | While I was using the chatbot for e-government services, I could freely choose the type of services I wanted. | |
| | AC3 | While I was using the chatbot for e-government services, I could freely inquire about the information that I wanted. | |
| | AC4 | While I was using the chatbot for e-government services, I did not feel that the program forced me to implement any option. | |
| | AC5 | I was in total control over the pace of my interaction with chatbots. | |
| Ubiquitous Computing | UC1 | I can access chatbots anytime to request e-government services. | Alalwan et al. (2020); Lee (2005) |
| | UC2 | I can use chatbots “anywhere”, and “anytime” at the point of need. | |
| | UC3 | I feel that I am always connected with chatbots as long as they are available over social media platforms (e.g., Facebook, WhatsApp). | |

(*continued on next page*)

**Table 2** (*continued*)

| Constructs | Code | Items | Sources |
|---|---|---|---|
| | UC4 | I can easily use with chatbots regardless of time and place. | |
| Synchronicity | SYN1 | The chatbot responds to my requests very quickly. | Alalwan et al. (2020) |
| | SYN2 | The chatbot responds to my requests immediately. | |
| | SYN3 | The chatbot responds to my requests without any delay. | |
| | SYN4 | The chatbot is fast in responding to my inquiries. | |
| Use | | Use Please choose your usage frequency for each of the following:<br>1) Seeking information on guidelines/ procedures for governmental transactions.<br>2) Inquiries about competitive ranking in the civil service bureau.<br>3) Inquiries about Fees for governmental transactions.<br>4) Inquiries about taxes.<br>5) Inquiries about traffic infractions.<br>6) Inquiries about government support for citizens in a particular area, such as energy consumption.<br>Note: Frequency ranged from "never" to "many times per day." | Venkatesh et al. (2012) |
| Satisfaction | SAT1 | The chatbot efficiently fulfilled tasks (e.g., seeking information) | Nguyen et al. (2021); Li et al. (2021) |
| | SAT2 | I am satisfied with the experience of using the chatbot for inquiry services. | |
| | SAT3 | I am satisfied with the experience of using the chatbot to complete governmental transactions. | |
| | SAT4 | Overall, I am satisfied with my experience of using the chatbot for e-government services. | |
| Continuance Intention | CI1 | I intend to continue using the chatbot for e-government services in the future. | Balakrishnan et al. (2022); Nguyen et al. (2021) |
| | CI2 | I will re-use the chatbot at the point of need. | |
| | CI3 | I plan to continue to use chatbots frequently for e-government services. | |
| | CI4 | I will always try to use chatbots for e-government services in my life. | |
| | CI5 | I would strongly recommend the chatbot to other citizens. | |

## Data availability

Data will be made available on request.

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