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The role of artificial intelligence in smart city systems usage: drivers, barriers, and behavioural outcomes

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ABSTRACT

Smart city and smart home systems are among the most impactful technological advancements of recent years, offering innovative solutions while also presenting new challenges for businesses and society. This study aims to investigate the antecedents (both drivers and barriers) of smart city system adoption, specifically those that incorporate artificial intelligence, and to analyse their effects on behavioral outcomes—more specifically, well-being and individual impact. The proposed model was tested using structural equation modelling with data from a survey of 211 individuals in Portugal. The main findings indicate that ubiquity and gamification were the most influential drivers of smart city system adoption. Conversely, perceived risks associated with these systems hindered their adoption. Additionally, our study demonstrated that trust significantly interacts with empowerment, perceived risk, and usage intention. Finally, usage intention was found to have a positive impact on well-being and individual outcomes in daily life.

1. Introduction

In recent years, smart home (SH) and smart city (SC) systems have emerged as some of the most significant technologies in our daily lives, seamlessly integrating into our environments and constantly present around us (Stojanović et al., 2023; Teng et al., 2024). These systems have expanded well beyond the domestic sphere into the public domain, with a particular emphasis on large, densely populated urban areas. Overall, the SC environment can be described as a space that leverages the Internet of Things (IoT) and data science to enhance the quality of life for its residents (Allam & Dhunny, 2019; Mikalef et al., 2022; Teng et al., 2024). Within these systems, real-time information exchange is possible, bringing both benefits and challenges related to data security (de Castro Neto & Rego, 2019). This is particularly relevant when these systems incorporate persuasive technologies, primarily powered by artificial intelligence (AI), enabling them to adapt to users' needs and behaviours (Herath & Mittal, 2022).

Although previous studies have explored the drivers and motivations behind individuals' adoption of AI-based smart city (SC) systems—often using models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) (Davis, 1986; Venkatesh & Davis, 2003; 2016)—further investigation is required to enhance our understanding of these drivers, as well as their outcomes. Several studies, including those by Arfi et al. (2021), Gansser and Reich (2021), Kumar et al. (2023), Teng et al. (2024), and Ullah et al. (2022), have contributed to this area, yet gaps remain.

For instance, Sanchez-Sepulveda et al. (2024) have argued that the rapid urbanization of major cities poses considerable challenges to residents' well-being, particularly concerning mobility patterns, infrastructure, and environmental pollution. Similarly, Mikalef et al. (2022) have proposed a "dark-side" perspective to analyse how AI is applied in practice, both to mitigate its potential negative consequences and to prioritise societal well-being—an approach consistent with Barbieri et al. (2025) and Bibri et al. (2024).

Although substantial research has examined the societal effects of urbanization, identifying and addressing critical urban areas remains a complex challenge. The aforementioned studies advocate for the adoption of data-driven urban strategies to support decision-making by urban planners, architects, and policymakers. These strategies focus on identifying key infrastructure areas to enhance mobility and foster social well-being.

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Therefore, this study aims to investigate both the antecedents (drivers and barriers) and the main outcomes of individuals' intention to use smart city (SC) systems that incorporate artificial intelligence (AI). This research is grounded in the belief-action-outcome framework, widely applied in information systems (IS) research (e.g., Mat Nawi et al., 2024; Melville, 2010; Ojo et al., 2019). Accordingly, the following three research questions are proposed.

RQ1. What are the drivers of individuals' intention to use AI-based SC systems?

RQ2. What factors influence the intention to use AI-based SC systems?

RQ3. How do AI-based SC systems impact perceived well-being and individual outcomes?

This study contributes to the field by identifying key drivers and barriers to the adoption of smart environments, particularly those reliant on artificial intelligence (AI). More specifically, the constructs of empowerment, user experience, and accessibility play a significant role in the adoption of smart city (SC) systems.

Secondly, it enhances understanding of the behavioural outcomes of SC system usage, particularly its effects on users' well-being and individual impact. Thirdly, our study demonstrates that trust significantly moderates both the antecedents and consequences of usage intention.

Finally, this study offers practical insights for professionals aiming to improve the acceptance and adoption of AI-driven SC systems through a user-centred approach, facilitating the development of strategies tailored to individuals' needs and motivations.

This paper is structured as follows: The next section outlines the theoretical background and prior research, followed by an introduction to the research model and hypotheses. The methodology is then detailed, leading to the main findings. Finally, the discussion section presents both theoretical and practical implications, as well as the study's limitations and recommendations for future research.

2. Theoretical background and related work

2.1. Smart cities systems and AI

The concept of smart cities is broad and lacks a precise definition within the research community. While it is generally understood as an interconnected, optimized, and knowledge-based high-density urban area (de Castro Neto & Rego, 2019), variations in implementation have led each city to develop its own definition. Table 1 presents different definitions of the smart city (SC) concept over the years. The growing popularity of smart cities and other smart systems has driven improvements in usability and security, facilitating greater user acceptance.

Table 1
Smart city definitions.

Definition	Source
The smart city is an organism with four know stages, being them the "initial stage" where it is defined what the city will become, "vertical" when small parts of the city start to gain autonomy and be connected to the web for information, "connected" when the city becomes interconnected among different services and finally "Growth engine" when the city becomes an ecosystem to boost growth and entrepreneurship with complete data transparency.	de Castro Neto and Rego (2019)
Smart Cities as an initiative is focused on trying to improve urban performance. Leveraging data, information, and information technologies (IT) to create more efficient services for its citizens, optimize and monitor infrastructure, improve collaboration, and encourage innovative business models in both the public and private sectors.	Marsal-Llacuna et al. (2015)
A smart city is a highly technical and advanced city that connects information, people, and city elements using new technologies to create a more sustainable, competitive, and innovative commerce, and a greater life quality.	Bakıcı et al. (2013)
A smart city is defined as one that employs ICT to raise productivity and quality of life to achieve urban sustainability	Teng et al. (2024)

Source: Authors own work

With the widespread adoption of the internet and the continuous advancement of smart technologies, efforts continue to develop more sophisticated systems capable of autonomously performing human actions. These systems primarily rely on artificial intelligence (AI), now enhanced by machine learning (ML) algorithms that enable more autonomous learning through deep neural networks, which simulate aspects of human brain perception. Over time, this high degree of autonomy has fostered a fear of innovation, stemming from these systems' ability to mimic human cognition and venture into uncharted territories. This, in turn, raises concerns about system security and challenges related to their acceptance.

On the other hand, it is also important to understand the potential improvements that can result from adopting these systems and how to develop new strategies to encourage individuals to participate in these intelligent networks. Although these advanced systems are not yet widely implemented, some smart city systems already leverage AI in daily operations. Overall, several areas are being affected by these advancements, including traffic, transportation, utilities, security, sustainability, and urban planning.

Regarding city-wide traffic management, dynamic routing and predictive traffic analysis are now widely integrated into GPS systems. These technologies assist by using real-time data to identify optimal routes and avoid congestion while also predicting future routes based on common traffic patterns. Other traffic management systems include adaptive traffic signals, which utilize sensors, cameras, and predictive analysis to regulate intersections and dual roads. In public transportation, fleet and schedule management systems help optimize routes, reduce bottlenecks, and enable real-time tracking of vehicles for more accurate pick-up and drop-off times (Dimitrakopoulos et al., 2020; Zannat & Choudhury, 2019).

In utility management, various systems support energy, water, and waste management. In energy management, these systems leverage smart grids to optimize energy distribution between sources and consumers, utilizing an array of sensors, meters, and weather forecasts. This enables the prediction of energy production and minimizes outages, helping to balance supply with demand. Additionally, AI plays a crucial role in integrating grids and renewable energy communities by forecasting weather patterns and optimizing system usage to ensure a continuous energy supply from intermittent sources (IEA, 2023; Serban & Lytras, 2020).

In water management, for instance, systems can optimize supply by adjusting water pressure based on user demand, as well as detecting and managing leaks. In waste management, automated sorting systems can reduce reliance on users' knowledge of waste separation. Additionally, bin monitoring technology not only enables smart scheduling of waste collection but also helps establish maintenance patterns for each area based on usage, conserving resources and preventing illegal waste dumping (Ali et al., 2020; Chaudhari et al., 2019, pp. 802–805).

To ensure public safety and security, cities can implement emergency response systems that provide emergency teams with real-time situational awareness through sensor networks (Huang et al., 2021). By analysing historical data, including patterns and locations, these systems help predict crime hotspots and support the implementation of preventive measures such as video surveillance and facial recognition systems (Tulumello & Iapaolo, 2022).

Regarding urban planning, leveraging AI-powered smart systems offers significant advantages, enabling the various management systems described above to contribute to the development of a truly intelligent urban environment (de Castro Neto & Rego, 2019). Effective traffic and public transport management are essential for designing a well-structured city capable of accommodating growth and handling large volumes of data in the future. Equally important is the integration of utility management to align supply with demand, with an emphasis on achieving self-sufficiency in resource production (Koumetio Tekouabou et al., 2023).

Integrating public safety into this design would help prevent the emergence of crime hotspots and ensure that, in the event of an emergency, reliable and efficient routes are available for emergency services. Land and zoning analysis is also crucial for determining the optimal placement of industrial, commercial, and residential areas within the city. Additionally, incorporating environmental planning is essential for fostering a greener, healthier urban environment that enhances overall quality of life (Burry, 2022; Yigitcanlar et al., 2020).

2.2. Prior research

Previous research on the acceptance of smart city systems utilizing advanced technologies remains somewhat fragmented. Regarding theoretical frameworks, the Technology Acceptance Model (TAM) (Davis, 1986) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh & Davis, 2003; 2016) are the most widely used. Table 2 summarizes the key factors examined in prior research. Studies have highlighted the significance of variables such as performance expectancy, effort expectancy, and social influence in shaping citizens' acceptance of advanced smart city systems (Arfi et al., 2021; Choi, 2022; Gansser & Reich, 2021; Ullah et al., 2022).

However, given the advanced capabilities of data collection and sharing, some researchers have also examined data privacy and security variables. For instance, studies have highlighted the relevance of perceived risk, fear, and insecurity in the acceptance of smart systems (Acheampong et al., 2021; Arfi et al., 2021; Distel et al., 2022; El Barachi et al., 2022; El-Haddadeh et al., 2019). Finally, from a different perspective, some studies have explored environmental factors as drivers of behavior. Researchers have, for example, incorporated environmental and social sustainability variables to understand sustainability-driven motivations (Abid et al., 2022; Zhang et al., 2022; Zhu et al., 2022).

Despite prior research, an opportunity remains to explore a less-developed phase: the impact of advanced smart city systems on citizens. Specifically, studies beyond the adoption and usage phases are limited, highlighting the need for further investigation into how these technologies affect citizens' lives (Sarker et al., 2019).

Table 2
Prior Research on the acceptance of smart city systems.

Theory	Variables	Source
UTAUT	Performance expectancy; Effort expectancy; Social influence; Facilitating conditions; Trust/mistrust; Perceived risk;	Arfi et al. (2021)
UTAUT2	Performance expectancy; Effort expectancy; Social influence; Cost saving; Environmental sustainability; Social sustainability; Health; Comfort; Security/insecurity; Habit; Hedonic motivations;	Gansser and Reich (2021)
TAM	Performance expectancy; Effort expectancy; Trust/mistrust; Cost saving;	Ullah et al. (2022)
TPB	Social influence; Attitude; Behavioural control;	Zhang et al. (2022)
SOR	Behavioural control; Unreliability/reliability; Responsiveness;	Zhu et al. (2022)
Others	Trust/mistrust; Empowerment; Technological advancement; Security/insecurity; Satisfaction;	El Barachi et al. (2022)
	Performance expectancy; Social influence; Privacy; Empowerment;	El-Haddadeh et al. (2019)
	Performance expectancy; Effort expectancy; Cost saving; Privacy; Unreliability/reliability; Service Quality;	Choi (2022)
	Effort expectancy; Social influence; Attitude; Behavioural control; Fear and anxiety; Benefits;	Acheampong et al. (2021)
	Social influence; Knowledge; Gamification;	Neves and Oliveira (2023)
	Smart decision making; Cost saving; Environmental sustainability; Social sustainability; Task performance;	Mariani et al. (2023)
	Social innovation; Smart decision-making; Technological advancement; Institutional quality; Environmental sustainability; Social sustainability;	Abid et al. (2022) Abid et al. (2022)
	Information exchange; Ubiquity; Autonomy; Usage intention; Satisfaction;	Yang and Lee (2023)

Source: Authors own work

2.3. The Belief-Action-Outcome (BAO) framework

The Belief-Action-Outcome (BAO) framework provides a conceptual lens for understanding how individual and collective beliefs shape actions and lead to specific outcomes. Initially developed to examine the interplay between information systems and environmental sustainability (Melville, 2010), the framework is structured around three interconnected pillars. Beliefs encompass the underlying assumptions, values, and perceptions that influence decision-making, while actions translate these beliefs into tangible behaviours or strategies, often mediated or moderated by contextual factors. Finally, outcomes refer to the resulting impacts, which may reinforce or challenge the initial beliefs, creating a feedback loop. This cyclical process makes the BAO framework particularly effective for analysing dynamic systems that require continuous adaptation and alignment.

Previous research has analysed the role of information systems using the BAO framework. For instance, Xu et al. (2024) examined how information systems (IS) can support community-based sustainability transformations. Based on a case study, they identified a process model grounded in the BAO framework. They proposed three key IS roles: participation objects, connectivity enablers, and fluctuation mitigators, providing insights and guidelines for similar initiatives. Similarly, Isensee et al. (2023) investigated the role of corporate culture in emission reduction within SMEs, using a steel construction SME in Germany as a case study. Applying the extended BAO framework, they identified corporate culture as both a driver and a barrier, outlining an informed approach that emphasizes vision development and the use of information systems to support sustainability efforts.

Using a similar approach, Ojo et al. (2019) investigated the cognitive and attitudinal factors influencing the adoption of Green Information Technology (GIT) among IT professionals in Malaysia. Applying the BAO framework, they identified the roles of GIT knowledge, social influence, and green management culture in shaping GIT attitudes, with partial mediation by beliefs, and confirmed the link between attitudes and green computing practices. Similarly, Mat Nawi et al. (2024) conducted a bibliometric review of 293 publications to analyse the knowledge structure of Green Information Technology (GIT) adoption and behavior. Two of the five identified clusters of studies were classified as studies based on the BAO framework.

Therefore, the BAO framework is well-suited for investigating the antecedents influencing the adoption of AI-driven smart city systems and their behavioral outcomes. As a foundational pillar, beliefs encapsulate individual, societal, and organizational perceptions of AI-driven smart city systems. Understanding these beliefs is critical for identifying key drivers and barriers, as they set the stage for subsequent actions.

Within the BAO framework, actions encompass both organizational strategies and individual behaviours aimed at integrating AI technologies. These actions may include investing in infrastructure, fostering partnerships, or initiating training programs to enhance AI literacy among users. Additionally, actions represent the translation of beliefs into tangible practices, such as individuals' intention to use AI-based smart city systems.

Outcomes, the final pillar, are assessed through measurable impacts on individual subjective well-being and broader societal benefits. For instance, AI-enhanced systems can improve urban mobility, reduce environmental footprints, and promote equitable resource distribution. At the individual level, outcomes may include perceived personal impact and subjective well-being.

By applying the BAO framework to smart city adoption studies, researchers can holistically map how initial beliefs (e.g., perceived empowerment and risk) drive specific actions (e.g., individuals' intention to use AI-based smart city systems) and ultimately result in outcomes affecting well-being and personal impact, as described next.

3. Research model

The model presented in Fig. 1 is based on the Belief-Action-Outcome (BAO) framework (Mat Nawi et al., 2024; Melville, 2010; Ojo et al., 2019), which explains how beliefs (antecedents) influence people's actions and, consequently, their outcomes. Specifically, the belief component includes variables that reflect individuals' perceptions of AI-driven smart city systems across two dimensions: drivers and barriers. This approach aligns with dual-factor theory, which examines phenomena from the perspective of enablers and inhibitors (Cenfetelli & Schwarz, 2011; Choi, 2022) and is consistent with studies on technology acceptance (Lin et al., 2015) and AI devices (Balakrishnan et al., 2021).

The action component is assessed through individuals' intention to use AI-driven smart city systems. The outcomes include perceived individual impact and users' subjective well-being. Finally, perceived trust in AI-driven smart city systems is proposed as a moderating factor in the relationship between beliefs, actions, and outcomes.

3.1. Drivers

As explained above, drivers are variables that positively influence individuals' intention to use AI-driven smart city systems. According to the literature, the selected drivers are empowerment, ubiquity, and gamification theory. Starting with empowerment, when users' choices, actions, and experiences in using or consuming a particular service create a sense of competence and knowledgeability, they typically feel empowered and tend to derive greater value from the service (El-Haddadeh et al., 2019; Füller et al., 2009; Porter & Donthu, 2008). Based on this, empowerment is incorporated into our model to provide insights into how individual engagement contributes to usage intention.

Additionally, ubiquity highlights the necessity and significance of networking in most smart cities. From a technological perspective, ubiquity is essential for enabling individuals to experience pervasive computing services on IoT devices (Angelidou, 2015). Thus, the ubiquitous characteristics of smart systems are among the core components that positively influence usage intention (Yang & Lee, 2023).

Finally, gamification refers to the incorporation of game design elements and mechanics into non-game contexts to enhance user engagement and facilitate the completion of challenging or monotonous tasks while ensuring an enjoyable interaction (Baptista & Oliveira, 2019). Within smart city systems, gamification aligns with behavioral patterns outlined in the Technology Acceptance Model (TAM) and its extensions (Davis, 1986; Venkatesh & Davis, 2003), particularly by enhancing perceived ease of use and enjoyment—two critical determinants of adoption. By fostering playful and rewarding interactions, gamified features transform utilitarian smart city systems into more engaging and intuitive experiences, thereby increasing both adoption and sustained use.

Practical applications of gamification in smart city systems demonstrate its potential impact. For example, apps like Waze incorporate gamified elements such as badges and points to incentivize users to provide real-time traffic updates, enhancing both system efficiency and user satisfaction. Similarly, Stockholm's 'Commute Greener' initiative utilized gamification to promote sustainable transportation by awarding points for eco-friendly commuting options such as cycling or public transit. These points were tracked on leaderboards, fostering a competitive and socially rewarding environment that encouraged widespread participation and contributed to reducing carbon footprints.

Beyond transportation, gamification can also be applied to waste management systems. For example, users may earn rewards for proper recycling, participate in neighbourhood recycling competitions, or receive virtual badges for consistently contributing to waste reduction goals. These mechanisms not only encourage individual behavior but also promote collective action toward broader societal objectives.

From a theoretical perspective, gamification enhances user engagement by appealing to intrinsic motivations such as achievement, social interaction, and mastery. Research suggests that individuals perceive gamified systems as more enjoyable and less burdensome, increasing their likelihood of participation (Neves & Oliveira, 2023, pp. 1–11). However, the success of gamification depends on its alignment with user preferences and cultural contexts, as poorly designed features may fail to resonate with diverse populations. Therefore, designing gamified elements that are accessible, inclusive, and tailored to the specific needs of smart city systems is crucial for maximizing their effectiveness.

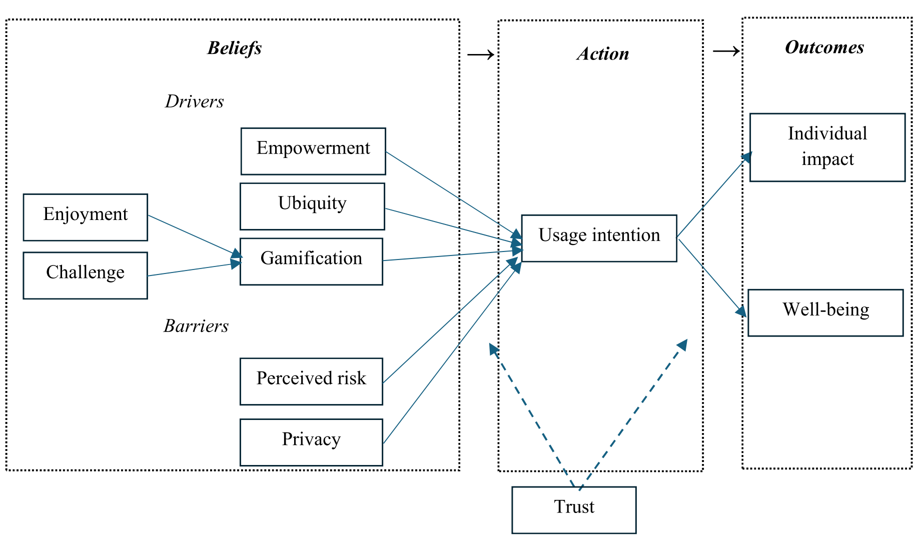

Fig. 1. – Conceptual model.
Note: Age, gender and income were control variables.
Source: Authors' own work.

In summary, gamification shows significant potential as a driver of user engagement in smart city systems by integrating functionality with enjoyment. Future research could examine its application in other domains, such as energy management and public safety, to further clarify its role in promoting sustained user adoption and active participation.

Based on this discussion, we propose the following hypotheses.

H1. Empowerment positively influences usage intention.

H2. Ubiquity positively influences usage intention.

H3. Gamification positively influences usage intention.

3.2. Barriers

Barriers are factors that negatively impact the intention to use these systems. This study primarily focuses on barriers related to data collection risks, specifically user-perceived risk and privacy concerns. Perceived risk refers to users' concerns about relying on a technology that may lead to data breaches, exploitation, or loss of control over the technology (Distel et al., 2022; Shuhaiber & Mashal, 2019). Risk may also act as a barrier to smart environment usage by fostering fear and mistrust among individuals. Regarding privacy concerns, users may worry that the platform lacks adequate security to protect sensitive or personal information (Arpaci et al., 2015; Habib et al., 2020; Zeng et al., 2023). Furthermore, the transmission of sensitive information across different systems in a smart city may create a perception of weak security and instil a sense of powerlessness in users (Choi, 2022; Habib et al., 2020).

Thus, we propose the following hypotheses.

H4. Perceived risk negatively influences usage intention.

H5. Privacy negatively influences usage intention.

3.3. Outcomes

Smart city systems offer multiple benefits, encompassing both performance-related outcomes and humanistic aspects, such as enhanced well-being. While Information Systems (IS) studies have highlighted a positive relationship between user behaviour and individual performance (e.g., Aparicio et al., 2019), they have largely overlooked performance outcomes. Furthermore, variables such as well-being have received insufficient attention in IS research.

Subjective well-being is defined as a state of life quality and satisfaction in which individual needs are met (Guillen-Royo, 2019; Mikalef et al., 2022). More specifically, Mikalef et al. (2022) proposed a 'dark-side' perspective to examine how AI is implemented in practice—not only to mitigate its potential negative consequences but also to incorporate societal well-being as a key requirement, an approach aligned with Barbieri et al. (2025) and Bibri et al. (2024). In this context, it is crucial to investigate the socio-technical structures and dynamics that contribute to the potential negative outcomes associated with AI and to identify areas where greater emphasis is needed to mitigate such risks.

Likewise, Sanchez-Sepulveda et al. (2024) have argued that the rapid urbanisation of major cities poses significant challenges to residents' well-being, particularly concerning mobility patterns, infrastructure, and environmental pollution. While extensive research has examined the societal effects of urbanisation, identifying and addressing critical urban areas remains highly complex. Their study advocates for the adoption of data-driven urban strategies to support decision-making by urban planners, architects, and policymakers, with a focus on identifying key infrastructure areas to improve mobility and promote social well-being. Based on the above discussion, we hypothesise.

H6. Usage Intention positively influences individual impact.

H7. Usage Intention positively influences subjective well-being.

3.4. Moderators

Smart city systems are characterised by the collection of vast amounts of data, which are sometimes perceived as risky (Shuhaiber & Mashal, 2019; Teng et al., 2024). Therefore, a key factor to consider is users' trust in the system, as this may influence their perception of the technology.

Trust is defined as a state of confidence that the technology will not harm the user in any way while also protecting their privacy (Arfi et al., 2021). Based on this, we argue that users with varying levels of trust may also exhibit different levels of motivation (Stojanović et al., 2023). Trust plays a crucial role in determining the likelihood of users adopting smart city systems (Habib et al., 2020; Teng et al., 2024). It significantly moderates user intentions, with higher levels of trust enhancing users' sense of empowerment and motivation to engage with the system (Flavián & Guinalíu, 2006; Ozkan & Kanat, 2011).

Hence, the moderating effect of trust is hypothesised to positively influence the drivers and their respective outcomes. Conversely, if users perceive the system as risky and doubt its ability to ensure the necessary privacy protections for their personal data, trust plays a different role. In such cases, it mitigates these concerns (Flavián & Guinalíu, 2006), making them less prominent and reducing their impact as barriers to usage. Thus, we hypothesise the following.

H8a. Trust moderates the relationship between empowerment and usage intention.

H8b. Trust moderates the relationship between ubiquity and usage intention.

H8c. Trust moderates the relationship between gamification and usage intention.

H8d. Trust moderates the relationship between perceived risk and usage intention.

H8e. Trust moderates the relationship between privacy and usage intention.

H8f. Trust moderates the relationship between usage intention and individual impact.

H8g. Trust moderates the relationship between usage intention and subjective well-being.

4. Methods

4.1. Measurement

This study involved the collection of quantitative data through a questionnaire to test the research model. An online questionnaire was administered to gather responses. The questionnaire was developed in both English and Portuguese and began with a brief introduction to the topic, followed by a multiple-choice question to determine which systems the respondents already used.

The items for each construct were identified and adapted accordingly. All questions were measured on a seven-point numerical scale (ranging from 1 = strongly disagree to 7 = strongly agree). Table 3 presents the item labels for each construct along with their respective sources. Age, gender, and income were included as control variables.

4.2. Data

The survey was conducted between May and June 2023 in Portugal. A total of 211 responses were collected; however, after data cleaning and processing, 144 (68%) were deemed useable and complete, which is considered satisfactory. Regarding the sample characteristics, most respondents (90%) were between 18 and 44 years old and predominantly female (62%). Additionally, the majority resided in urban areas (83%)

Table 3
Constructs, items, sources, and measurement properties.

Constructs	Items	Source
Trust α = 0.81 CR = 0.88 AVE = 0.64	I trust in the technology used by Smart Cities Systems containing Artificial Intelligence. I trust in the ability of Smart Cities Systems containing Artificial Intelligence to protect my privacy. Using Smart Cities Systems containing Artificial Intelligence is financially secure. I am not worried about the security of Smart Cities Services containing Artificial Intelligence	(Arfi et al., 2021; Ullah et al., 2022)
Perceived Risk α = 0.88 CR = 0.92 AVE = 0.80	Using Smart Cities Systems containing Artificial Intelligence seems risky. I feel that using Smart Cities Systems containing Artificial Intelligence would cause me a lot of trouble if something went wrong. Basically, I'm sure I would make a mistake if I used Smart Cities Systems containing Artificial Intelligence.	Arfi et al. (2021)
Privacy α = 0.80 CR = 0.88 AVE = 0.70	Smart Cities Systems containing Artificial Intelligence should not sell my personal information to other companies. Smart Cities Systems containing Artificial Intelligence should not share my personal information with other companies unless I am specifically authorized to do so. Smart Cities Systems containing Artificial Intelligence should not use my personal information for any purpose not specifically authorized by me.	(El-Haddadeh et al., 2019; Gansser & Reich, 2021)
Empowerment α = 0.84 CR = 0.90 AVE = 0.75	I feel enthused to actively use Smart Cities Systems containing Artificial Intelligence. Using Smart Cities Systems containing Artificial Intelligence would give me a feeling of accomplishment. With the use of Smart Cities Systems containing Artificial Intelligence, I am able to manage my everyday life activities better.	El-Haddadeh et al. (2019)
Ubiquity α = 0.67 CR = 0.82 AVE = 0.60	I should be able to access Smart Cities Systems containing Artificial Intelligence through mobile devices, wearables, transportation, kiosks, and other various devices. It should be convenient to use Smart Cities Systems containing Artificial Intelligence while moving from place to place or when doing anything else. Ubiquity is an outstanding advantage of Smart Cities Systems containing Artificial Intelligence.	Yang and Lee (2023)
Enjoyment α = 0.92 CR = 0.95 AVE = 0.86	I find using Smart Cities Systems containing Artificial Intelligence to be enjoyable. The process of using Smart Cities Systems containing Artificial Intelligence seems pleasant. I should have fun using Smart Cities Systems containing Artificial Intelligence.	Aparicio et al. (2019)
Challenge α = 0.71 CR = 0.83 AVE = 0.63	The Smart Cities Systems containing Artificial Intelligence should provide "hints" in the text that help me overcome the challenges. The Smart Cities Systems containing Artificial Intelligence should provide "online support" that helps me overcome the challenges. The Smart Cities Systems containing Artificial Intelligence should provide video or audio auxiliaries that help me overcome the challenges.	Aparicio et al. (2019)
Usage Intention α = 0.93 CR = 0.95 AVE = 0.87	I intend to use Smart Cities Systems containing Artificial Intelligence in the future. I predict I would use Smart Cities Systems containing Artificial Intelligence in the future. I would recommend others to use Smart Cities Systems containing Artificial Intelligence.	Yang and Lee (2023)
Well-being α = 0.93 CR = 0.95 AVE = 0.83	Smart Cities Systems containing Artificial Intelligence satisfy my overall needs. Smart Cities Systems containing Artificial Intelligence play a very important role in my social well-being. Smart Cities Systems containing Artificial Intelligence play a very important role in my leisure well-being. Smart Cities Systems containing Artificial Intelligence play an important role in enhancing my quality of life.	El Hedhli et al. (2013)
Individual Impact α = 0.91 CR = 0.94 AVE = 0.84	Smart Cities Systems containing Artificial Intelligence enables me to accomplish tasks more quickly. The use of Smart Cities Systems containing Artificial Intelligence could increase my productivity. The use of Smart Cities Systems containing Artificial Intelligence could make it easier to accomplish tasks. The use of Smart Cities Systems containing Artificial Intelligence could be useful for my job.	Aparicio et al. (2019)

Notes – α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.
Source: Authors own work

and had attained at least a secondary school education (99%).

In terms of net monthly income per individual, the largest proportion of respondents reported earning less than 1000 euros (37%), followed by those in the 1000 to 2000 euros range (33%). These figures align with Portugal's income distribution characteristics (Rodrigues, 2023).

In addition to socio-demographic characteristics, it was also possible to assess the use of specific smart city systems across various application areas, including traffic and energy. The most commonly used smart city systems are traffic-related applications, such as transit, parking, ride-sharing, and bike-sharing apps. The second most utilized category is energy-related systems, particularly smart meters and green initiative apps. Fig. 2 illustrates the distribution of respondents' usage of smart city systems.

Two approaches were employed to assess common method bias. First, Harman's single-factor test was conducted (Podsakoff et al., 2003), using factor analysis to confirm that the first component accounted for less than 50% of the variance. Second, an irrelevant marker variable was introduced, revealing a maximum shared variance of 5.6% with other variables, which falls within the acceptable range. Based on these results, no significant common method bias was detected.

The partial least squares (PLS) statistical technique was used to estimate the research model, as PLS is suitable for small sample sizes (Ke et al., 2009) and does not require normality assumptions (Fornell &

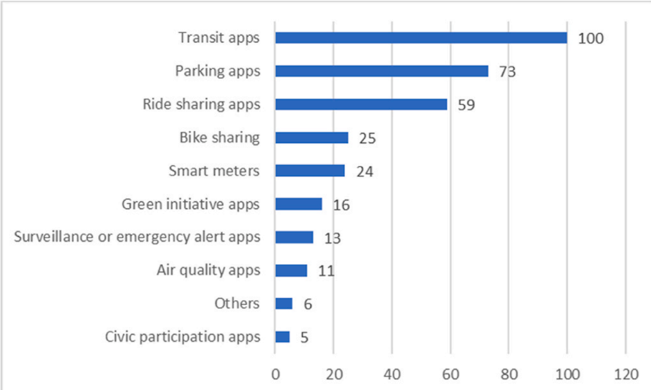

Fig. 2. Smart city systems usage.
Source: Authors' own work

Bookstein, 1982). First, the measurement model was tested for reliability, as well as for convergent and discriminant validity. Subsequently, the structural model was tested. SmartPLS® 4.0 was used.

5. Results

5.1. Measurement properties

To evaluate the measurement model, a detailed analysis was conducted using three statistical measures: Cronbach's alpha, composite reliability, and average variance extracted (AVE). As shown in Table 3, Cronbach's alpha values exceeded 0.60, composite reliability values were above 0.70, and AVE values were greater than 0.50, thereby confirming convergent validity (Fornell & Larcker, 1981; Hair et al., 2019).

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT), the Fornell-Larcker criterion, and cross-loadings. According to the Fornell-Larcker criterion, discriminant validity is established when the correlation between two constructs is lower than the square root of the AVE of each construct (Fornell & Larcker, 1981). As shown in Table 4, correlations were lower in all comparisons, confirming discriminant validity.

Table 4 also presents the HTMT test, where values below 0.85 confirm discriminant validity between reflective constructs (Hair et al., 2019). For the eight cases (out of forty-five pairs) where values exceeded 0.85, discriminant validity was verified by analysing the confidence intervals of the specific HTMT values, ensuring they excluded 1 (see footnote in Table 4). Additionally, the loadings and cross-loadings met the required conditions, as all loadings were higher than the corresponding cross-loadings (Chin, 1998), as shown in the Appendix. Overall, these findings confirm discriminant validity.

5.2. Structural model test

The structural model, incorporating the antecedents and consequences of usage intentions, as well as the proposed moderator (Fig. 1), was tested using a bootstrapping approach with 5000 iterations. This method facilitated the calculation of path coefficients and their statistical significance (Hair et al., 2019). The model explained 82% of the variance in usage intention, 75.5% of the variance in individual impact, and 64.3% of the variance in perceived well-being.

We used the adjusted R^2 to compare the two estimated models (i.e., with vs. without the moderator), as it is not influenced by the number of variables. As shown in Table 5, the second model, which incorporates trust as a moderator, demonstrates greater explanatory power for usage intention and its associated outcomes, reinforcing the notion that trust plays a significant role in understanding the user and their intentions. Consequently, eight out of fourteen hypotheses were supported.

Regarding the drivers, two of the three antecedents were significantly associated with usage intention. Specifically, gamification exhibited a positive and significant effect ($\lambda = 0.483$) on usage intention, supporting H3. A similar pattern was observed for ubiquity, which also had a positive and significant effect ($\lambda = 0.157$) on usage intention, supporting H2. Conversely, the influence of empowerment on usage intention was not significant at the 5% level, thus not supporting H1. The coefficient ($\lambda = 0.126$) was significant only at the 10% level. As shown in Table 5, after accounting for trust, the effect of empowerment was no longer statistically significant.

Concerning the barriers, perceived risk was statistically significant, supporting H4, with a negative coefficient ($\lambda = -0.229$), indicating that higher perceived risk is associated with lower usage intention of AI-based smart city (SC) systems. Conversely, privacy did not have a significant influence on usage intention ($\lambda = -0.10$), thus not supporting H5. This finding aligns with the low correlation between the two variables ($r = 0.27$).

Furthermore, usage intention had a positive and significant effect on individual impact ($\lambda = 0.652$) and subjective well-being ($\lambda = 0.502$), supporting H6 and H7. This suggests that respondents with a higher intention to use AI-based SC systems also report a greater perceived individual impact and subjective well-being.

Finally, regarding the moderating effects, the findings indicate that trust significantly interacted with empowerment and perceived risk in influencing usage intention, supporting H8a and H8d. Additionally, trust significantly interacted with usage intention to affect individual impact, supporting H8f.

Regarding the interaction between trust and perceived risk (H8d), Fig. 3 illustrates that individuals with high levels of trust continue to intend to use AI-based SC systems, even when these systems are

Table 4
Discriminant validity.

	1	2	3	4	5	6	7	8	9	10
1. Challenge	**0.79**	0.73	0.84	0.74	0.54	0.47	0.63	0.66	0.82	0.70
2. Empowerment	057	**0.87**	0.92[a]	0.82	0.16	0.33	0.91[c]	0.65	0.84	0.90[f]
3. Enjoyment	069	0.82	**0.93**	0.92[b]	0.23	0.48	0.85	0.59	0.94[d]	0.87[g]
4. Ind Impact	0.60	0.72	0.84	**0.92**	0.23	0.42	0.78	0.56	0.93[e]	0.86[h]
5. Privacy	0.39	0.13	0.20	0.21	**0.84**	0.32	0.15	0.65	0.31	0.05
6. Perceived Risk	−0.37	−0.27	−0.43	−0.38	−0.27	**0.90**	0.26	0.25	0.53	0.25
7. Trust	0.51	0.75	0.76	0.69	0.05	−0.13	**0.80**	0.47	0.74	0.83
8. Ubiquity	0.47	0.49	0.47	0.45	0.50	−0.20	0.36	**0.77**	0.59	0.48
9. Usage Intention	0.67	0.76	0.87	0.85	0.27	−0.47	0.67	0.48	**0.93**	0.79
10. Well-being	0.57	0.79	0.80	0.79	0.02	−0.22	0.73	0.38	0.75	**0.91**

Notes – Values in the diagonal are the square root of AVE; values below the diagonal are the correlations, and above the diagonal are the HTMT values. For those HTMT values greater than 0.85, the confidence interval did not include 1, as expected.

[a] Confidence interval (CI): 0.872–0.966; b. CI: 0.863–0.963; c. CI: 0.832–0.974; d. CI: 0.905–0.976; e. CI: 0.863–0.974; f. CI: 0.838–0.957; g. CI: 0.808–0.911; h. CI: 0.797–0.908.

Source: Authors own work

Table 5
Test of the proposed model.

	Hypotheses	Model 1 Coefficients	Model 2 (with moderators) Coefficients
Direct effects			
H1	EMP → UI	0.248**	0.126
H2	U → UI	0.046	0.157*
H3	Gamification → UI	0.584**	0.483**
H4	PR → UI	−0.122**	−0.229**
H5	P → UI	0.01	−0.10
H6	UI → II	0.838**	0.652**
H7	UI → W	0.766**	0.502**
(a)	C → gamification	0.413**	0.126
(a)	ENJ → gamification	0.67**	0.413**
Moderators			
H8a	T × EMP → UI		−0.126*
H8b	T × U → UI		0.061
H8c	T × gamification → UI		0.126
H8d	T × PR → UI		0.207**
H8e	T × P → UI		−0.094
H8f	T × UI → II		−0.048*
H8g	T × UI → W		0.022
Controls			
T → II			0.195**
T → UI			0.085
T → W			0.409**
Age → II		−0.075	−0.085
Age → UI		−0.015	−0.003
Age → W		0.058	0.022
Gender → II		−0.017	−0.025
Gender → UI		−0.061	−0.047
Gender → W		0.056	0.029
Income → II		−0.101	−0.082
Income → UI		0.058	0.019
Income → W		−0.105	−0.039
Adjusted R^2 of UI		77.0%	82.0%
Adjusted R^2 of II		72.8%	75.5%
Adjusted R^2 of W		57.1%	64.3%

(*$p < 0.05$; **$p < 0.01$).
Notes – C — Challenge; Emp — Empowerment; Enj — Enjoyment; II — Individual Impact; P — Privacy; PR — Perceived Risk; T — Trust; U — Ubiquity; UI — Usage Intention; W — Well-being; (a) Gamification is a second-order construct.
Source: Authors own work

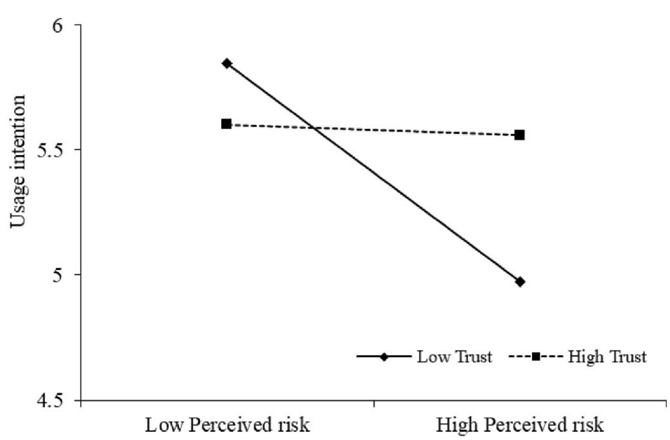

Fig. 3. Trust × Perceived Risk interaction.
Source: Authors' own work

perceived as highly risky. In contrast, those with low levels of trust exhibit a decline in usage intention as perceived risk increases.

Fig. 4 illustrates the interaction between trust and empowerment (H8a), demonstrating that higher empowerment leads to a greater intention to use technologies. However, when an individual's trust in technology increases, their usage intention remains high, even when

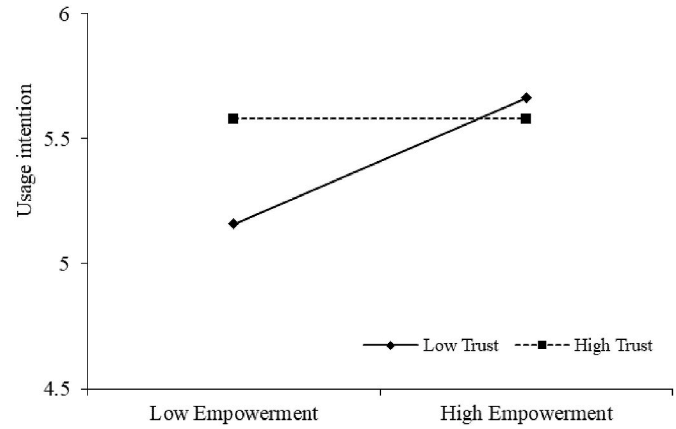

Fig. 4. Trust × Empowerment interaction.
Source: Authors' own work

perceived empowerment is low.

Finally, Fig. 5 illustrates the interaction between trust and usage intention (H8f). The findings suggest that an increase in usage intention is associated with a greater perceived individual impact, which is more pronounced among users with high trust in AI-based SC systems.

6. Discussion

As we progress into new technological eras and witness advancements in artificial intelligence within the context of smart cities, it is essential to understand users' willingness to adopt and engage with these systems, as well as their behavioural outcomes (Grundner & Neuhofer, 2021; Mikalef et al., 2022). By examining the key drivers, barriers, and outcomes influencing the intention to use AI-integrated smart city systems, the empirical research presented here offers valuable insights.

6.1. *Key findings*

First, the analysis of the drivers indicated that two of the three proposed antecedents—ubiquity and gamification—positively and significantly influenced the usage intention of AI-based smart city (SC) systems, contributing to the existing literature (Neves et al., 2024; Yang & Lee, 2023). Our study highlights the importance of ensuring that technology remains universally accessible across both temporal and spatial contexts, leveraging its ubiquitous properties to mitigate situations where users may feel disempowered due to an inability to connect

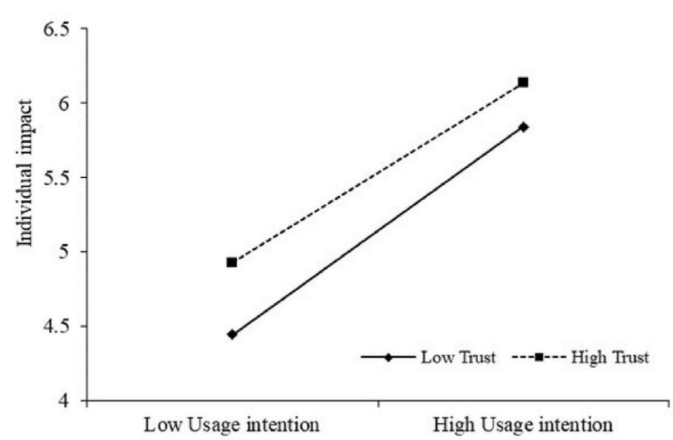

Fig. 5. Trust × Usage Intention interaction.
Source: Authors' own work

to the system (Yang & Lee, 2023). Indeed, users are generally more willing to adopt technologies when they perceive an enhancement in their ability to perform daily tasks, fostering a sense of accomplishment. Conversely, empowerment was not a significant driver after controlling for trust as a moderator, underscoring the critical role of trust in the analysis of AI-based SC systems. Notably, an interaction was observed between trust and empowerment, as discussed below.

Moreover, integrating game-like features into smart city systems, given their advanced intelligence, could significantly enhance the user experience by making interactions not only more intuitive but also more engaging. It is important to reduce system mechanisation and introduce a more interactive and user-friendly interface. The findings from our study suggest that when these technologies prioritise extending user capabilities and providing accessible and enjoyable interactions, users are more likely to adopt them, aligning with the conclusions of Baptista and Oliveira (2019).

Second, concerning the barriers to usage intention, perceived risk had a negative and significant effect, as expected, aligning with the revised literature (Shuhaiber & Mashal, 2019). Our research indicates that users' primary concerns revolve around the risk of human error being exploited by third parties, as well as the system's ability to effectively address potential flaws that could cause harm to individuals. This perception leads users to view the technology as risky, resulting in a loss of control or power and increasing their sense of vulnerability (Shuhaiber & Mashal, 2019). The analysis also suggested that the effects of perceived risk are relatively substantial, ranking second only to gamification, highlighting its relevance as a key antecedent.

On the other hand, the findings suggested that privacy was not a significant antecedent of usage intention. The lack of significance of privacy concerns in this study can be attributed to various contextual and psychological factors. One possible explanation lies in the regulatory framework of the European Union, where stringent data protection regulations, such as the General Data Protection Regulation (GDPR), are firmly established. These regulations impose strict privacy standards, fostering a sense of trust and security among users. As a result, individuals operating within such environments may perceive institutional safeguards as sufficient to mitigate privacy risks, thereby reducing the prominence of privacy concerns in their decision-making (Hamon et al., 2022).

Another plausible explanation relates to the phenomenon of 'privacy calculus,' whereby individuals assess and balance the trade-offs between privacy risks and the perceived benefits of technology adoption. Research suggests that users often prioritise the tangible advantages of AI-driven systems—such as convenience, efficiency, and quality of life improvements—over potential privacy concerns (Chen et al., 2024; Guerra et al., 2024). In the context of smart city systems, features such as enhanced mobility, optimized energy usage, and improved public safety may offer compelling value propositions that outweigh privacy apprehensions.

However, it is important to note that this dynamic may vary in regions with weaker regulatory frameworks or lower levels of public awareness regarding data protection. In such contexts, privacy concerns may become more pronounced, significantly influencing user behaviour (Teng et al., 2024). Future research should investigate these variations by examining populations across diverse regulatory, cultural, and technological environments to provide a more comprehensive understanding of privacy's role in the adoption of smart city systems.

Third, the findings on behavioural outcomes—individual impact and subjective well-being—highlight the significant role of smart city systems in enhancing both personal and societal dimensions. Users perceive that their contribution to society is amplified through the use of these technologies. Simultaneously, their subjective well-being improves, encompassing user satisfaction, the fulfilment of personal needs, and overall quality of life (Mikalef et al., 2022). The substantial effect sizes observed (standardised coefficients exceeding 0.5) underscore the strong influence of usage intention on these outcomes, reinforcing their relevance in the context of smart city systems. This contribution addresses a notable gap in the information systems literature, where performance outcomes have been underexplored (Aparicio et al., 2019).

Behavioural outcomes, such as subjective well-being, can be assessed through metrics including life satisfaction, perceived stress reduction, and improvements in daily mobility. These metrics reflect how smart city systems enhance convenience and efficiency in users' lives, thereby improving their overall quality of life. For instance, transportation systems with real-time traffic updates reduce commute times and associated stress, while energy management platforms lower utility costs, contributing to financial well-being.

At a broader societal scale, these outcomes have significant implications. The equitable distribution of resources enabled by smart city technologies promotes inclusivity and reduces disparities in access to essential services. Likewise, the adoption of energy-efficient systems supports environmental sustainability by lowering carbon emissions and encouraging responsible consumption patterns. Moreover, enhanced urban connectivity through integrated systems facilitates community cohesion and social interaction, strengthening the social fabric of urban environments.

These findings highlight the essential role of smart city systems in addressing both individual and collective needs. By integrating features that prioritise user satisfaction and societal benefit, these technologies have the potential to significantly enhance quality of life. Future research could build upon these insights by exploring additional behavioural metrics, such as mental health indicators, healthcare system effectiveness, or community engagement, to provide a more comprehensive understanding of the societal transformations driven by smart city technologies, thereby advancing the existing literature (e.g., Barbieri et al., 2025).

Finally, trust plays a crucial role in moderating the relationship between perceived risks, key drivers, and user behaviour in the adoption of AI-driven smart city systems. As illustrated in Fig. 3, our findings indicate that trust mitigates the negative impact of perceived risks on usage intention. Specifically, individuals with high levels of trust maintain consistent usage intentions even when perceived risk is elevated, demonstrating trust's buffering effect. Conversely, those with lower trust levels exhibit a significant decline in usage intention under high-risk perceptions, highlighting the vulnerability created by insufficient trust.

Fig. 4 illustrates trust's moderating influence on empowerment, demonstrating that low levels of trust weaken the positive effect of empowerment on usage intention. Conversely, for individuals with high trust, the impact of empowerment on usage intention is amplified, suggesting that trust not only reinforces user confidence but also enhances their sense of agency. This relationship indicates that trust acts as a catalyst, transforming potential drivers into actionable motivations.

Fig. 5 illustrates the moderating effect of trust on the relationship between usage intention and individual impact. Users with high trust derive amplified benefits from their engagement with smart city systems, resulting in a greater perceived individual impact. This dynamic underscores the dual role of trust: mitigating perceived risks while enhancing the positive outcomes associated with system usage.

These findings contribute to the existing literature on smart city adoption (Habib et al., 2020; Stojanović et al., 2023; Teng et al., 2024), highlighting trust's dual role as both a mitigator of risks and an enabler of adoption. By reducing perceived risks while enhancing drivers such as empowerment and ubiquity, trust fosters a stable and conducive environment for system adoption across diverse user groups. The results further underscore the importance of trust-building measures, including transparent communication, participatory design processes, and robust data protection frameworks. Such initiatives can strengthen user confidence, lower adoption barriers, and maximise the potential of AI-driven smart city systems for widespread implementation and meaningful societal impact.

6.2. Theoretical contributions

The present study makes significant theoretical contributions to the expanding body of research on artificial intelligence (AI) within smart city systems, drawing on the belief-action-outcome (BAO) framework. By integrating and advancing this conceptual approach, the study not only corroborates previous findings (e.g., Mikalef et al., 2022; Zhou et al., 2023) but also introduces novel insights that address critical gaps in the literature.

Firstly, this research enhances the nuanced understanding of the drivers and barriers influencing users' adoption of AI-based smart city systems. Identifying ubiquity and gamification as primary facilitators reinforces the dual-factor theory, which highlights the coexistence of enablers and inhibitors in technology adoption (Choi, 2022). However, unlike prior studies that have often examined these factors in isolation, our findings underscore the dynamic interplay between these drivers and contextual elements, particularly trust. The moderating role of trust reveals its dual function as both a catalyst and a mitigator of user perceptions, offering a more refined perspective on its influence in smart city environments (Stojanović et al., 2023). More specifically, this study extends existing literature by demonstrating how trust can shape user empowerment, transforming it from a latent enabler into an actionable determinant of usage intention (Habib et al., 2020; Teng et al., 2024).

Secondly, the study's examination of barriers, particularly perceived risk, provides new insights into the psychological and social constraints influencing technology adoption. While previous research has generally acknowledged risks as obstacles, our findings clarify the mechanisms through which perceived risks interact with trust, either exacerbating or alleviating users' concerns. This contribution advances theoretical understanding by demonstrating that risk perception is not a static barrier but a dynamic construct shaped by contextual factors (Distel et al., 2022). Conversely, privacy concerns did not significantly affect usage intention, suggesting a potential desensitisation effect among users accustomed to ubiquitous AI applications. This nuanced finding challenges conventional assumptions and highlights the need for further research into the evolving role of privacy in digital environments (Zeng et al., 2023).

Thirdly, this research contributes to the relatively underexplored domain of behavioural outcomes associated with smart city systems. By empirically demonstrating the positive effects of usage intention on individual well-being and societal engagement, the study bridges the gap between adoption-focused research and outcome-oriented analyses. The strong effect sizes observed for both individual impact and subjective well-being highlight the transformative potential of smart city systems, extending the literature on technology-mediated quality-of-life improvements (Aparicio et al., 2019; Mikalef et al., 2022). Furthermore, the interaction between trust and outcomes, whereby higher trust amplifies individual impact, provides a theoretical foundation for designing systems that prioritise user confidence.

Lastly, this study validates the applicability of the BAO framework within the context of smart city systems, reinforcing its utility as a robust theoretical model for examining the interconnections between beliefs, actions, and outcomes. By contributing to the empirical validation of the BAO framework (Isensee et al., 2023; Melville, 2010; Xu et al., 2024), this research provides a comprehensive foundation for future studies investigating complex socio-technical phenomena in urban settings. Moreover, by integrating dual-factor theory and contextual moderators within the BAO structure, the study enhances the framework's capacity to capture the nuanced dynamics of smart city adoption and impact.

6.3. Practical implication

This study offers several practical implications for policymakers, urban planners, and technology developers seeking to enhance the adoption and impact of AI-integrated smart city systems. By addressing both the drivers and barriers of usage intention, the findings provide actionable insights for designing more user-centric and trustworthy smart city environments.

First, the identification of ubiquity and gamification as key drivers highlights the necessity of creating systems that are accessible, engaging, and seamlessly integrated into users' daily lives. Policymakers and developers should prioritise the deployment of ubiquitous computing technologies to ensure system availability at any time and location. For instance, investments in robust IoT infrastructures can enhance the reliability and accessibility of smart city services. Additionally, incorporating gamification elements into system interfaces can transform routine interactions into engaging experiences, fostering sustained user participation. This approach is particularly relevant in public services such as transportation and waste management, where user involvement directly impacts system efficiency.

Second, the critical role of trust as a moderator underscores the necessity of transparent and secure system design. Organisations must not only implement but also effectively communicate stringent data protection measures to alleviate concerns about perceived risks. Explicit regulatory compliance—such as adherence to GDPR or equivalent frameworks—should be conveyed through clear privacy policies and accessible information channels.

Moreover, integrating features like real-time feedback mechanisms and error detection systems can enhance user confidence by demonstrating the reliability and accountability of AI-driven processes. These measures are particularly crucial in high-risk applications, such as facial recognition for public safety or predictive analytics for energy management, where concerns over misuse and errors are more pronounced.

Third, the study's findings on barriers, particularly perceived risks, suggest that public awareness campaigns and educational initiatives are essential for reducing fear and uncertainty surrounding smart city systems. Governments and organisations can collaborate to develop outreach programmes that inform citizens about the benefits and safeguards of these technologies. Such efforts could include workshops, interactive demonstrations, and digital literacy programmes to demystify AI applications. Additionally, highlighting successful implementations of AI-based systems in other cities can serve as a persuasive tool for building user trust and reducing scepticism. Indeed, collaboration and co-creation have remained a challenge in the smart city context.

Fourth, the demonstrated positive impacts of usage intention on individual well-being and societal contributions highlight the need to prioritise user-centric design principles. Developers should create interfaces and functionalities that enhance user satisfaction and align with their needs. For instance, systems can incorporate adaptive personalisation features that cater to diverse user preferences and contexts. Urban planners can leverage these insights to design smart city initiatives that address not only operational efficiency but also quality-of-life improvements, such as equitable access to resources and enhanced mobility solutions.

Lastly, the attenuation of privacy concerns observed in the study suggests that users may become more accepting of AI systems over time, particularly when provided with visible safeguards. However, continuous engagement with stakeholders is essential to ensure that these concerns do not resurface with technological advancements or changes in regulatory landscapes.

7. Conclusions

The adoption of technology, particularly smart city systems integrating artificial intelligence, has garnered significant attention in recent years. This focus aims not only to refine the market orientation of these technologies but also to understand how to encourage citizen adoption and identify the reasons behind the failure of certain approaches. Therefore, this study facilitates the identification of both the drivers and barriers influencing the intention to use these systems.

Concerning the drivers, ubiquity and gamification emerged as the most relevant factors. Conversely, among the barriers, perceived risk was significant, whereas privacy concerns were not. It is, therefore, crucial for manufacturers, organisations, and municipalities to enhance the drivers while mitigating the barriers. If managed effectively, this approach can improve the user experience and ensure the necessary security measures are in place for individuals using AI-based smart city systems.

Regarding the limitations, this study focuses on the perception of artificial intelligence within the smart city context, without considering its implications for smart domestic environments such as smart homes, smart assistants, and autonomous vehicles. Future research could investigate the impact of artificial intelligence on a smaller scale and examine its implications when used in more private settings.

Additionally, this study was conducted in Portugal, a developed European nation with high digital literacy and robust data protection regulations, including the General Data Protection Regulation (GDPR). These contextual factors likely influenced respondents' perceptions of the drivers, barriers, and outcomes associated with the adoption of AI-integrated smart city systems. Consequently, the findings may not fully reflect the dynamics in regions with different regulatory frameworks, levels of digital literacy, or trust in institutions.

Cultural differences may also play a significant role in shaping adoption patterns. For example, in collectivist societies, where communal values often take precedence, community-wide benefits may outweigh the emphasis on individual empowerment, potentially altering the relative importance of drivers such as ubiquity. In contrast, more individualistic cultures may prioritise features that enhance personal autonomy and customisation. Likewise, societal attitudes towards technology adoption—ranging from openness to innovation to risk aversion—may further mediate the relevance of specific drivers and barriers.

Economic disparities represent another critical dimension. In less developed regions, infrastructural limitations and affordability constraints may heighten barriers such as perceived risk or limit access to smart city systems. These challenges could significantly affect adoption intentions, necessitating localised strategies to address resource constraints and infrastructural gaps.

Future research should examine these dimensions using a cross-cultural and comparative approach to validate the proposed model across diverse regional contexts. For example, studies conducted in emerging economies or regions with varying levels of technological adoption, digital infrastructure, and regulatory stringency would yield valuable insights. Additionally, incorporating contextual variables such as economic development indices, cultural dimensions, and governance frameworks could provide a more comprehensive understanding of the factors facilitating or obstructing the adoption of smart city systems on a global scale.

Finally, although privacy concerns were muted in this study, we acknowledge that this may not be universally applicable across all populations or settings. Future research could examine variations in privacy perceptions across different demographic, cultural, and regulatory contexts. Additionally, longitudinal studies may provide insights into how evolving regulatory landscapes and emerging technologies influence the significance of privacy concerns over time.

CRediT authorship contribution statement

Joao Pedro Ferreira dos Santos: Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Celso Augusto de Matos:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Aleš Groznik:** Visualization, Validation, Supervision, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Loadings and Cross-Loadings

	C	Emp	Enj	II	P	PR	T	U	UI	W
C1	**0.849**	0.496	0.562	0.447	0.357	−0.203	0.438	0.390	0.527	0.502
C2	**0.731**	0.356	0.413	0.380	0.270	−0.269	0.259	0.445	0.420	0.379
C3	**0.794**	0.493	0.638	0.580	0.313	−0.404	0.482	0.303	0.632	0.471
Emp1	0.489	**0.908**	0.765	0.667	0.096	−0.29	0.668	0.44	0.68	0.694
Emp2	0.47	**0.798**	0.608	0.511	0.062	0.004	0.678	0.337	0.483	0.701
Emp3	0.531	**0.893**	0.731	0.68	0.169	−0.345	0.633	0.471	0.758	0.686
Enj1	0.658	0.771	**0.944**	0.762	0.182	−0.432	0.68	0.453	0.831	0.741
Enj2	0.636	0.734	**0.907**	0.774	0.144	−0.402	0.702	0.396	0.793	0.718
Enj3	0.623	0.761	**0.93**	0.793	0.224	−0.359	0.73	0.461	0.796	0.778
II1	0.569	0.674	0.761	**0.894**	0.107	−0.334	0.617	0.348	0.738	0.774
II2	0.505	0.635	0.74	**0.91**	0.199	−0.324	0.625	0.395	0.77	0.709
II3	0.578	0.683	0.803	**0.948**	0.255	−0.383	0.666	0.481	0.831	0.702
P1	0.322	0.067	0.138	0.113	**0.848**	−0.211	−0.043	0.356	0.177	−0.042
P2	0.267	0.169	0.181	0.223	**0.843**	−0.20	0.102	0.47	0.273	0.053
P3	0.431	0.074	0.17	0.159	**0.825**	−0.28	0.028	0.404	0.209	0.013
PR1	−0.328	−0.298	−0.393	−0.34	−0.28	**0.904**	−0.105	−0.164	−0.421	−0.225
PR2	−0.362	−0.265	−0.402	−0.346	−0.189	**0.878**	−0.173	−0.213	−0.409	−0.251
PR3	−0.312	−0.173	−0.362	−0.334	−0.261	**0.907**	−0.064	−0.161	−0.441	−0.131
T1	0.52	0.704	0.734	0.656	0.114	−0.20	**0.84**	0.359	0.654	0.659
T2	0.36	0.607	0.591	0.51	−0.047	−0.091	**0.788**	0.333	0.516	0.604
T3	0.436	0.581	0.648	0.626	0.118	−0.192	**0.847**	0.295	0.618	0.57
T4	0.249	0.473	0.377	0.357	−0.099	0.203	**0.714**	0.084	0.267	0.487
U1	0.242	0.333	0.312	0.293	0.445	−0.108	0.201	**0.762**	0.351	0.227
U2	0.565	0.362	0.426	0.383	0.422	−0.295	0.238	**0.783**	0.431	0.294

(continued on next page)

(*continued*)

	C	Emp	Enj	II	P	PR	T	U	UI	W
U3	0.221	0.45	0.341	0.355	0.272	−0.012	0.413	**0.778**	0.312	0.368
UI1	0.599	0.72	0.801	0.81	0.201	−0.417	0.62	0.397	**0.938**	0.687
UI2	0.643	0.63	0.8	0.767	0.29	−0.515	0.579	0.434	**0.923**	0.627
UI3	0.642	0.761	0.833	0.803	0.267	−0.396	0.679	0.508	**0.937**	0.767
W1	0.529	0.761	0.801	0.848	0.053	−0.237	0.689	0.377	0.777	**0.90**
W2	0.474	0.711	0.658	0.622	0.03	−0.152	0.634	0.298	0.581	**0.896**
W3	0.499	0.697	0.703	0.66	−0.026	−0.199	0.686	0.356	0.622	**0.928**
W4	0.576	0.707	0.748	0.727	0.004	−0.218	0.649	0.34	0.712	**0.914**

Notes – C — Challenge; Emp — Empowerment; Enj — Enjoyment; II — Individual Impact; P — Privacy; PR — Perceived Risk; T — Trust; U — Ubiquity; UI — Usage Intention; W — Well-being.
Source: Authors own work

Data availability

Data will be made available on request.

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