UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER'S THESIS

Ljubljana, August 2023 JOÃO PEDRO FERREIRA DOS SANTOS

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AN ANALYSIS OF THE ROLE OF ARTIFICIAL INTELLIGENCE IN EUROPEAN SMART CITIES

Ljubljana, September 2023 JOÃO PEDRO FERREIRA DOS SANTOS

AUTHORSHIP STATEMENT

The undersigned JOÃO PEDRO FERREIRA DOS SANTOS, a student at the University of Ljubljana, School of Economics and Business, (hereafter: SEB LU), author of this written final work of studies with the title AN ANALYSIS OF THE ROLE OF ARTIFICIAL INTELLIGENCE IN EUROPEAN SMART CITIES, prepared under supervision of red. prof. dr. Aleš Groznik and co-supervision of researcher dr. Celso Matos.

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LIST OF ABBREVIATIONS

sl. – Slovene

AI – (sl. Umetna Inteligenca); Artificial Intelligence

DS – (sl. Podatkovna Znanost); Data Science

ICT – (sl. Informacijske in Komunikacijske Tehnologije); Information and communication Technology

IoT – (sl. Internet Stvari); Internet of Things
ML – (sl. Strojno Učene); Machine Learning
SC – (sl. Pametno Mesto); Smart City
SEM – (sl. Modeliranje Strukturnih Enačb); Structural Equation Model
SH – (sl. Pametni Dom); Smart Home

ABSTRACT

This research focuses on understanding what drives users to adopt smart city systems, particularly those that incorporate artificial intelligence as their primary driver, and what outcomes we can derive from it. I studied how technology acceptance impacts consumers' lives. I splitted the antecedents into drivers and barriers to usage intention and studied how they affect behavioral outcomes. My model was tested with a survey of 211 Portugal consumers. I used structural equation modeling technique to show that the constructs of feelings of power, user experience, and accessibility played a significant role in adoption of smart city systems. Perceived risks associated with smart city systems hindered the adoption. Finally, the usage intention has a positive impact on both wellbeing and performance in their daily life.

KEYWORDS

Artificial Intelligence; Smart Cities; Structural equation modeling; Consumer behavior

1 INTRODUCTION

In the last few years, smart home (SH) and smart city (SC) systems are becoming one of the most important technologies, and consequently environments, in our daily life, being able to surround us constantly. These systems are becoming increasingly trendy as the years go by and are showing a large expansion into the public domain and out of the already-known private/domestic environment with a particular emphasis on large and densely populated urban areas. Overall, the SC environment can be described as a space that takes advantage of the Internet of Things (IoT) and data science to provide better life quality to its members (de Castro Neto & Rego, 2019). On these systems, it is possible to have a real-time interchange of information, raising both benefits but also concerns about data security (Dhillon et al., 2016). This is particularly true when these systems are comprised of persuasive kinds of technology, mainly based on artificial intelligence (AI) and machines to learn, mimic, and adapt their features to the user needs and behavior (Wilson et al., 2015). Having this, the study of both benefits and obstacles is of main importance.

Most studies regarding AI-based SC systems focus primarily on identifying the drivers or motivations to get consumers to use these systems. However, studies that investigate the outcomes we can get from the adoption of these systems are very scarce. The mainly used theories for understanding user behavior are rather dated and widely used, namely the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) (Davis, 1986; Venkatesh et al., 2003)(Davis, 1986; Venkatesh et al., 2003). To fill this gap, our work is grounded on the belief-action-outcome (BAO) framework to understand both antecedents (drivers and barriers as beliefs) as well as outcomes of the usage intention of AI-based SC systems as the action. Thus, the following three research questions are studied:

RQ1: What are the drivers for the individuals' usage intention of AI-based SC systems?

RQ2: What is the overall perception and intention to use AI-based SC systems?

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

Overall, this study contributes to the identification of the main benefits and risks of the adoption of smart environments when these systems rely mostly on AI and Machine Learning (ML) to operate, making them, for their vast majority, independent of human surveillance and intervention. Secondly, it contributes to the research on technologies' impacts on several types of outcomes since post-adoption and usage studies are still in an early stage. Finally, it helps practitioners to better understand the acceptance and usage of advanced smart environments, based on the users' perspective, thus creating strategies that are customized to consumer needs and motivations.

This study is structured as follows. The next section presents the background research on the systems already available and prior research on them. Then, the research model and the development of the hypotheses. After, the data and methodology are presented, followed by the results. Finally, we present the discussion, together with both practical and theoretical implications, as well as the limitations and future research.

2 THEORETHICAL BACKGROUND AND RELATED WORK

2.1 Smart Cities Systems and AI

Smart city concepts are still quite broad without an accurate definition by the research community. Although it is generally viewed as an interconnected, optimized, and knowledge-based high-density urban area (de Castro Neto & Rego, 2019), the differences within each concept are mainly due to the variances in implementation, making each city develop its particular definition. Table 1 shows some different definitions of the SC concept through the years. The growing popularity of this and other smart systems made them improve their usability, as well as their security to be accepted by consumers.

Table 1: Smart City Definition

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 & Rego, 2019)
The smart city has a model composed of six dimensions. Those dimensions are mobility, people, economy, environment, government, and living, being all interconnected with the citizen taking a central place inside these dimensions.	(Khatoun & Zeadally, 2016)
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 to 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)

To be continued

Table 1: Smart City Definition (cont.)

Definition	**Source**
The idea of a smart city is grounded in the creation and connection of human and social capital, and information and communication technology (ICT) infrastructure to create a greater and more sustainable economic development sustaining a better quality of life.	(Manville et al., 2014)
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 greater life quality.	(Bakıcı et al., 2013)
Smart city can be defined broadly as to the search and identification of intelligent solutions to allow modern cities to improve the quality of the services to aware citizens as Smart.	(Giffinger et al., 2007)

Source: Own Work

With the widespread use of the internet and the ever-growing access to new and better smart technologies, we keep on trying to develop better systems that can perform human actions without human interference. Mostly these systems are comprised of AI, with the new addition of ML algorithms to help them learn more autonomously with the use of Deep Neural Networks, capable of simulating parts of the human brain perception. This large degree of autonomy, with time, leads to fear of novelty: the capability of such systems to mimic the human mind and to leap forward toward the unknown, creating a concern around the system's security and difficulty in accepting these systems. On the other hand, it is also important to understand which improvements can be determined through the acceptance of these systems and how to create new ways to target consumers, so they are more willing to be part of these intelligent networks.

Although these types of advanced systems are not yet widely spread, it is possible to identify some examples of smart city systems that take leverage of AI daily. Overall, several areas are being affected by these changes, such as traffic, transportation, utilities, security, sustainability, urban planning, etc.

Regarding traffic management for city-wide use, dynamic routing, and predictive traffic analysis are widely used on GPS systems nowadays, both as supporters, with the use of real-time data to identify the best routes to avoid traffic congestion (Nikitas et al., 2020), as well as a predictor for future routes based on usual patterns of those paths (Abduljabbar et al., 2019). Other systems that influence traffic are adaptive traffic signals that use sensors cameras and predictive traffic analysis to manage intersections and dual roads. On public transport, we can have fleet and schedule management to help to create optimal routes avoiding traffic bottlenecks or even having real-time tracking for a given vehicle to arrive for pick-up and drop-off (Dimitrakopoulos et al., 2020; Zannat & Choudhury, 2019).

On utility management, we have systems for energy, water, and waste management. For energy management, these systems take advantage of the smart grid for the optimization of energy between sources and consumers, using an array of sensors and meters as well as weather forecasts. This allows us to predict production and minimize outages, helping to balance supply according to demand. AI can also be a useful tool to help users to integrate grids and renewable energy communities by predicting weather patterns and advising on the use of systems to allow intermittent sources to provide a continuous flow of energy (IEA, 2023; Serban & Lytras, 2020). In water management, there is the ability to optimize supply allowing fluctuation in water pressurization depending on user demand, as well as to predict leakage and manage leaking courses (Alam, 2021; Rojek & Studzinski, 2019). Finally, on waste management, we could have sorting systems that help to reduce reliability on users' knowledge of sorting their waste, bin monitorization that besides allowing for smart planning of pick-ups would also create maintenance patterns for each area depending on their usage, allowing to save resources and to prevent illegal waste dumping (Ali et al., 2020; Chaudhari et al., 2019).

For public safety and security, cities can rely on emergency response systems that could trigger emergency teams to have total awareness of events with the use of sensor networks (Huang et al., 2021). Through the analysis of historical data such as patterns and locations, it is possible to predict crime hotspots and allocate proactive policing such as video surveillance and facial recognition systems (Alsamhi et al., 2019; Tulumello & Iapaolo, 2022).

Regarding urban planning, the usage of smart systems relying on AI would be advantageous by using the various management systems described above to plan and create an urban environment capable of itself being smart (de Castro Neto & Rego, 2019). Traffic and public transport management are crucial to have a well-designed and well-planned city that is capable to withstand its growth and that can manage the high volumes of data in the future, as well it is important to integrate utility management to create supply for the demand of the city itself with focus on it being self-sufficient on their production (Koumetio Tekouabou et al., 2023). Being able to integrate public safety in this design would prevent the possibility of crime hotspots and manage to, in the face of any emergency, create fast and reliable routes for emergency services to reach the locations in need. Land and zoning analysis is important to identify how to spawn industrial, commercial, and residential areas to more suitable locations within the city, and lastly be aware of environmental planning to create a greener, but also healthier city increasing quality of life (Burry, 2022; Yigitcanlar et al., 2020).

2.2 Prior Research

Regarding previous research on the acceptance of smart cities systems, using advanced technologies, research is somewhat fragmented. In terms of theories used, the technology acceptance model (TAM) (Davis, 1986) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) are the main ones. Table 2 summarizes the main factors used in prior research. Researchers found the significance of variables like performance expectancy, effort expectancy, and social influence on citizens' acceptance of advanced smart cities systems (Arfi et al., 2021; Choi, 2022; Gansser & Reich, 2021; Ullah et al., 2022). However, given the advanced capability of collecting and sharing data, some other authors have also investigated variables related to data privacy and security. For example, some authors found the relevance of perceived risk, fear, and insecurity in accepting smart systems (Acheampong et al., 2021; Arfi et al., 2021; El-Haddadeh et al., 2019; El Barachi et al., 2022). Finally, in a different perspective than the above ones, some studies have also investigated environmental factors as drivers of behavior. For example, authors have used variables like environmental sustainability, and social sustainability to understand sustainable-based motivations (Abid et al., 2022a; Mariani et al., 2023; Zhang et al., 2022; Zhu et al., 2022).

Table 2: Prior Research

Used theory(ies)	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 & Reich, 2021)
TAM	Performance expectancy; Effort expectancy; Trust/mistrust; Cost saving;	(Ullah 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; Behavioral control; Fear and anxiety; Benefits;	(Acheampong et al., 2021)
	Social influence; Knowledge; Gamification;	(Neves & Oliveira, 2023)
TPB	Social influence; Attitude; Behavioral control;	(Zhang et al., 2022)

to be continued

Table 2: Prior Research (cont.)

Used theory(ies)	Variables	Source
SOR	Behavioral control; Unreliability/reliability; Responsiveness;	(Zhu et al., 2022)
	Smart decision making; Cost saving; Environmental sustainability; Social sustainability; Task performance;	(Mariani et al., 2023)
Others	Trust/mistrust; Empowerment; Technological advancement; Security/insecurity; Satisfaction;	(El Barachi et al., 2022)
	Social innovation; Smart decision-making;	(Abid et al., 2022b)
	Technological advancement; Institutional quality; Environmental sustainability; Social sustainability;	(Abid et al., 2022a)
	Information exchange; Ubiquity; Autonomy; Usage intention; Satisfaction;	(Yang & Lee, 2023)

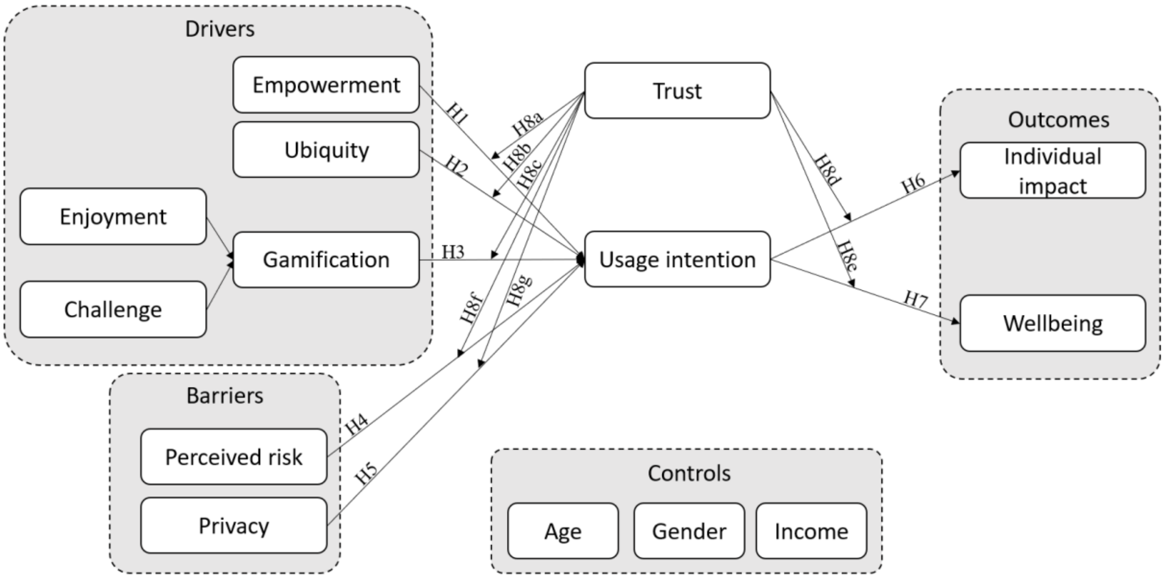
Source: Own Work

Given this, it is clear that there is still room to explore other theories that have not yet been examined in the field but mainly contribute to a phase that is not yet developed – the impact these advanced smart city systems might have on citizens. Phases beyond adoption and use are still scarce, and there is a need to increase studies on the impacts of technologies on citizens' lives (Sarker et al., 2019).

3 RESEARCH MODEL

The model presented in Figure 1 is based on the belief-action-outcome framework (Melville, 2010) which can effectively explain behaviors and their final outcomes. This happens by explaining how beliefs (antecedents) influence peoples' actions and consequently their outcomes. Regarding the antecedents, we have based on the dual factor theory, which examines the phenomenon from the perspective of enables and inhibitors (Cenfetelli & Schwarz, 2011). This theory has been used in several topics, such as job satisfaction (Herzberg et al., 2017) and acceptance of technologies (Lin et al., 2015), namely AI devices (Balakrishnan et al., 2021).

Figure 1: Research Model



Source: Own Work

3.1 Drivers

Drivers, as explained above, are based on variables that positively affect and influence consumers' usage intention. According to the literature, the chosen drivers are empowerment, ubiquity, and gamification theory. Beginning with empowerment, it is noticeable that when users' choices, actions, and experiences in using or consuming a particular service create a feeling of competence and knowledgeability, they usually feel empowered and tend to create value from this service (El-Haddadeh et al., 2019; Füller et al., 2009; Porter & Donthu, 2008). Based on that, empowerment is exploited for our model by offering insights on how consumer engagement effectively contributes to their usage intention. Additionally, ubiquity emphasizes in most smart cities the need for and importance of networking. From a technological point of view, ubiquity is necessary to allow consumers to experience pervasive computing services on IoT devices (Angelidou, 2015). Thus, the ubiquitous characteristics of smart systems are among the core components to positively influence their usage intention(Yang & Lee, 2023). Finally, the gamification concept is the ability to include game techniques and features in a non-game context, to help individuals perform hard and strenuous tasks while keeping an entertaining interaction (Baptista & Oliveira, 2019). Furthermore, users tend to dislike routines and prefer when they view them as games that can capture their interest (Neves & Oliveira, 2023). Thus, we hypothesize the following:

H1: Empowerment positively influences usage intention;

H2: Ubiquity positively influences usage intention;

H3: Gamification positively influences usage intention;

3.2 Barriers

Barriers are the variables that will have a negative impact on the usage intention with these systems. The barriers chosen for this study are mainly based on the risk of collecting data. Therefore, the user-perceived risk and privacy concerns will be analyzed. Perceived risk can be understood as the users' concern to rely on a technology that might lead to a data breach, exploitation, and even loss of control over the technology (Shuhaiber & Mashal, 2019). The risk might also create a barrier to smart environment usage since it creates fear and mistrust in the consumer (Elian, 2022). Regarding privacy concerns, consumers might worry that the platform is not secure enough to keep sensitive or personal information (Arpaci et al., 2015; Habib et al., 2020). Thus, the risks of the transmission of sensitive information among different systems in a smart city will create the sensation of weak security in the system and give the user a sense of powerlessness (Choi, 2022; Habib et al., 2020). Hence, the following hypothesis are proposed:

H4: Perceived risk negatively influences usage intention;

H5: Privacy negatively influences usage intention;

3.3 Outcomes

In terms of outcomes, smart city systems provide several benefits, both in terms of performance, but also humanistic ones, such as wellbeing. Overall, IS studies have overlooked performance outcomes (e.g. Aparicio et al., 2019) showing a positive relationship between user behavior and individual performance. However, variables like wellbeing have been under-looked in IS. Wellbeing can be defined as a state of life quality and satisfaction, where individual needs are met (Guillen-Royo, 2019). Based on this, we hypothesize that smart city systems can have a positive impact on both types of outcomes. The following is hypothesized:

H6: Usage Intention positively influences individual impact;

H7: Usage Intention positively influences wellbeing;

3.4 Moderator

Smart city systems are characterized by collecting a great amount of data, being sometimes perceived as risky (Shuhaiber & Mashal, 2019). Therefore, one main factor to take into consideration is the users' trust in the system, as this might influence their perception of the technology. Trust can be defined as a state of confidence that the technology will not harm the user by any means, also protecting the user's privacy (Arfi et al., 2021). Based on this, we believe that users with distinct levels of trust can also show distinct levels of motivation. Given that trust is important to understand how likely are the users to be driven into using smart city systems (Habib et al., 2020), we can understand then that the user intention is largely moderated by this level of trust and that the higher the level of trust the more empowered and compelled to get into the system the user will be (Flavián & Guinalíu, 2006; Ozkan & Kanat, 2011). Hence, the moderator effect of trust can be hypothesized as being positive towards not only the drivers but their respective outcomes. On the other hand, we have concerns about the system, think of it as risky and that it might not be capable of handling the necessary privacy in order to protect our personal data, then trust plays a different role, since it mitigates/hinders these concerns (Flavián & Guinalíu, 2006) making them less evident and reducing their impact as barriers of the usage. Thus, we hypothesize 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 wellbeing;

3.5 Controls

Consumer behavior study is often controlled by some variables. Given that smart city systems are considered an advanced type of technology, it is important to control the results, regarding a set of variables, especially socio-demographic ones. Therefore, age, gender, and income were used as control variables for this research model.

4 METHODOLOGY

4.1 Measurement

This study required the collection of quantitative data through a questionnaire to test the research model. An online questionnaire was conducted as a way to collect responses. The questionnaire was developed both in English and Portuguese and it started with a brief introduction to the topic and a multiple-answer question to understand which systems the individuals already used (see Appendix A). The items from each construct were identified and adapted accordingly. The questions were measured on a seven-point numerical scale (ranging from 1 – strongly disagree to 7 – strongly agree). Table 3 presents the items per construct and the respective source.

Table 3: Constructs & Items

Construct	Items	Source
Trust	I trust in the technology Smart Cities Systems containing Artificial Intelligence are using. 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	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	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)

To be continued

Table 3: Constructs & Items (cont.)

Construct	Items	Source
Empowerment	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	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 & Lee, 2023)
Enjoyment	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	The Smart Cities Systems containing Artificial Intelligence should provide "hints" in text that helps 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	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 & Lee, 2023)

To be continued

Table 3: Constructs & Items (cont.)

Construct	Items	Source
Well-being	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	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)

Source: Own Work

4.2 Data

Table 4: Sample Characteristics

Characteristics	Sample data
Age	
18-24	32%
25-34	35%
35-44	24%
45-55	6%
55-64	4%
>64	0%
Gender	
Female	62%
Male	38%
Other	1%
Area	
Urban	83%
Rural	17%

To be continued

Table 4: Sample Characteristics

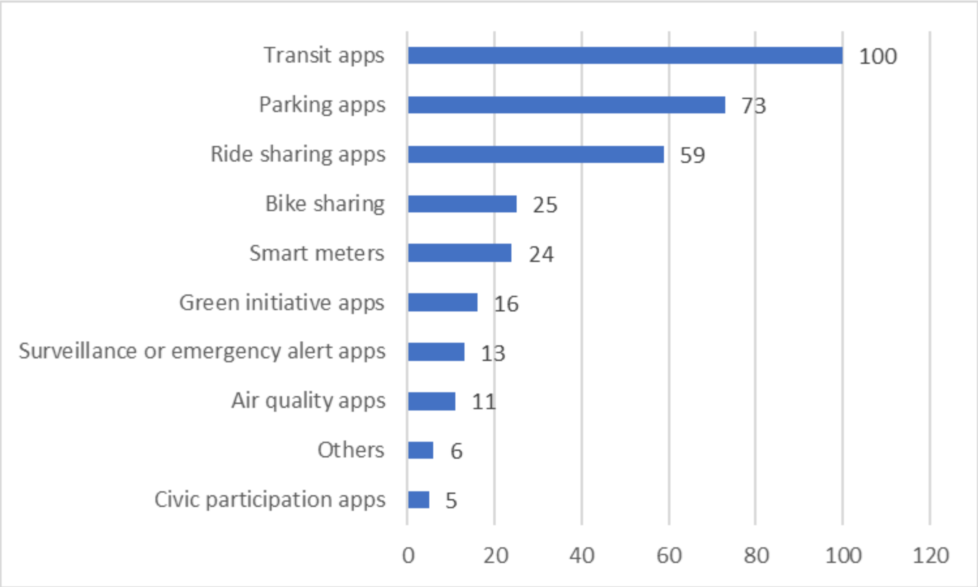
Characteristics	Sample data
Education	
No school	0%
Primary school	1%
Secondary school	22%
Bachelor	43%
Master	33%
PhD	1%
Income	
<1000€	37%
1000€-2000€	33%
2000€-3000€	6%
3000€-4000€	1%
4000€-5000€	0%
>5000€	23%

Source: Own Work

The survey was conducted during May-June 2023 in Portugal. A total of 211 responses were collected, however, after data cleaning and treatment, 144 (68%) were found usable and complete, which is considered satisfactory. Regarding sample characteristics, most respondents (90%) have age between 18 and 44 years, predominantly female (62%). Also, most respondents live in urban areas (83%) and have, at least, secondary school (99%). In terms of net monthly income per individual, the majority of respondents answered in the categories of lower than 1000 euros (37%), followed by 1000 to 2000 euros (33%), which is in agreement with Portugal's characteristics in terms of income (Rodrigues, 2023)(Rodrigues, 2023). Table 4 presents the sample characteristics.

Besides socio-demographic characteristics, it was also possible to measure the use of specific smart city systems in the various areas of application, from traffic to energy, etc. Therefore, the most used are traffic apps, namely transit, parking, ridesharing, and bike-sharing apps. The second most used area of smart city systems is on energy, specifically smart meters, and green initiative apps. Figure 2 presents the distribution of the smart city systems usage by the respondents.

Figure 2: Smart City Systems usage



Source: Own Work

Furthermore, it was examined the common method bias for the responses in two different ways, the first approach was through the use of Harman's one-factor test (Podsakoff et al., 2003) using factor analysis the first component would explain less than 50% of the variance. After it was added an irrelevant marker variable (Lindell & Whitney, 2001), it was validated that this marker had a maximum shared variance with other variables of 5.6% which is considered to be a reasonable value (Johnson et al., 2011). Due to the performed tests, it was concluded that no significant common method bias is indicated.

The partial least squares (PLS) statistical technique was used to estimate the research model. This technique ended up being chosen since it is good for small sample sizes and to try models that have not been tested prior (Ke et al., 2009), which is the case of this study, as we try to provide inside into new Inputs to the usage intention of AI-based SC systems, as well as predict some of its outcomes. Pls is a great technique to use in this case as it doesn't require any assumption to restrict distribution (Fornell & Bookstein, 1982), this requirement is possible to verify, establishing the suitability to use the PLS technique. To begin, the model was tested regarding reliability and discriminant validity, and only after are we able to test the structural model itself. For this study and its purposes, Smart PLS 4.0 was used.

5 RESULTS

5.1 Data

To assess the measurement model various measures were analyzed. On Table 5 it is possible to observe the average variance extracted (AVE) where all constructs have and AVE higher than 0.5 confirming convergent validity (Fornell & Larcker, 1981; Hair et al., 2012). The Heterotrait-Monotrait Ratio (HTMT), Fornell-Larcker criterion, and cross-loadings were used to assess discriminant validity. The Fornell-Larcker criterion can ensure discriminant validity when the diagonal elements, AVE square root, are higher than the constructs correlation (Fornell & Larcker, 1981) as we can observe on Table 5.

Table 5: Fornell-Larcker Table

	Cronbach's alpha	*C*	*Emp*	*Enj*	*II*	*P*	*PR*	*T*	*U*	*UI*	*W*
C	0.705	**0.793**									
Emp	0.838	0573	**0.868**								
Enj	0.918	0689	0.815	**0.927**							
II	0.906	0.6	0.724	0.837	**0.918**						
P	0.795	0.398	0.133	0.198	0.206	**0.839**					
PR	0.878	-0.372	-0.272	-0.429	-0.379	-0.272	**0.897**				
T	0.813	0.508	0.751	0.759	0.693	0.047	-0.126	**0.799**			
U	0.672	0.469	0.488	0.471	0.447	0.499	-0.199	0.356	**0.774**		
UI	0.925	0.673	0.756	0.87	0.851	0.271	-0.473	0.673	0.479	**0.933**	
W	0.930	0.573	0.792	0.804	0.792	0.017	-0.224	0.732	0.379	0.746	**0.97**

Source: Own Work

The diagonal elements above represent the square root of AVE. C – Challenge; Emp – Empowerment; Enj – Enjoyment; II – Individual Impact; P – Privacy; PR – Perceived Risk; T – Trust; U – Ubiquity; UI – Usage Intention; W – Wellbeing;

Table 6: 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	0.39	0.527	0.502
C2	**0.731**	0.356	0.413	0.38	0.27	-0.269	0.259	0.445	0.42	0.379
C3	**0.794**	0.493	0.638	0.58	0.313	-0.404	0.482	0.303	0.632	0.471

To be continued

Table 6: Loadings and Cross-Loadings (cont.)

	C	*Emp*	*Enj*	*II*	*P*	*PR*	*T*	*U*	*UI*	*W*
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**	-0.2	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	-0.2	**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
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	**0.9**
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**

Source: Own Work

We can verify from the loadings and cross-loadings condition is satisfied, presented in Table 6, given by PLS confirmatory factor analysis, by having all loadings being higher than the cross-loadings (Chin, 1998).

Table 7, which represents HTMT, where the values below 0.9 ensure the discriminant validity between reflective constructs and the ones who are above 0.9, we could ensure their validity since the confidence intervals of these values are below 1. Proving that the reflective constructs can be used to test the structural model.

Table 7: Heterotrait-Monotrait ratio (HTMT)

	C	*Emp*	*Enj*	*II*	*P*	*PR*	*T*	*U*	*UI*	*W*
C										
Emp	0.733									
Enj	0.843	0.92								
II	0.741	0.818	0.918							
P	0.536	0.164	0.227	0.228						
PR	0.469	0.329	0.479	0.424	0.327					
T	0.63	0.908	0.85	0.782	0.15	0.256				
U	0.656	0.645	0.589	0.564	0.653	0.254	0.466			
UI	0.822	0.835	0.944	0.928	0.305	0.526	0.738	0.594		
W	0.699	0.903	0.866	0.857	0.052	0.247	0.832	0.48	0.795	

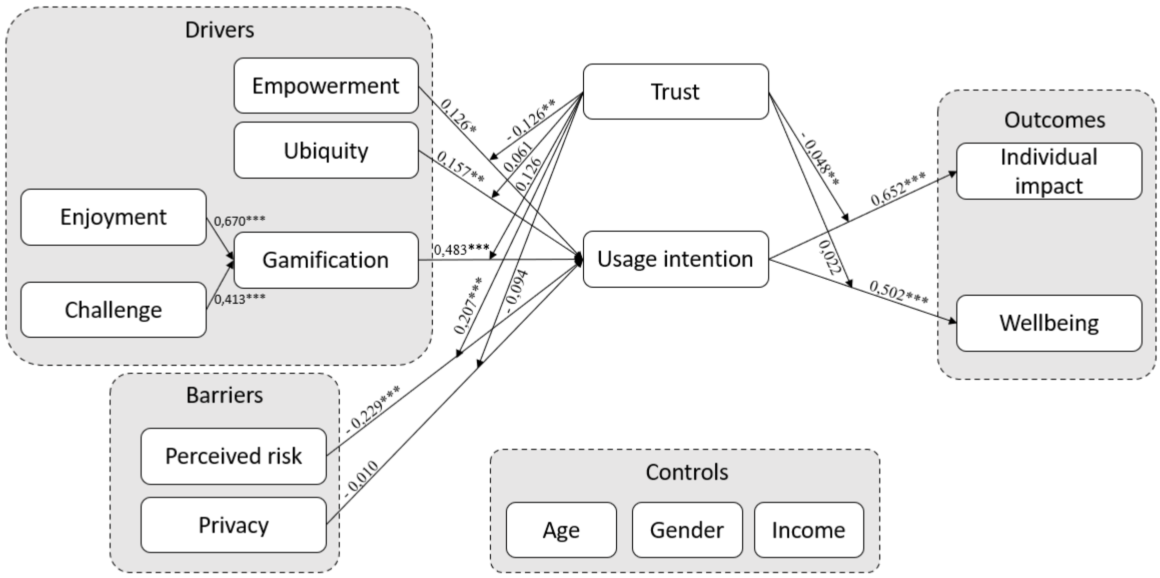
Source: Own Work

5.2 Structural Model

The structural model (Figure 3) presents us with the direct effects of the usage intention, the direct effect of the usage intention, and the explained variation. Bootstrapping with 5000 iterations of resampling was performed to assess the significance of the effects (Hair et al., 2012). The model explains 83.8% of the variation in usage intention, 76.5% of the variation of individual impact, and 65.8% of the variation of perceived wellbeing. All hypotheses about the drivers were supported. Regarding the barriers', only perceived risk was statistically significant. Therefore, H5 was not supported. Usage intention presents a strong positive impact on the outcomes, supporting H6 and H7. Finally, regarding the moderator effect, H8a, H8d, and H8f were supported. Hence, 9 out of 14 hypotheses were supported.

To evaluate the model presented in Figure 3, in order to understand the moderator effect, we used the adjusted R2 since it is more robust to compare different models, since it does not rely on, nor it is affected by the number of used variables. As presented in Table 8, the second model, which uses trust as a moderator, has a greater explicative power to the usage intention and the outcomes presented by it, strengthening the belief that trust plays a significant role to understand the user and its intentions.

Figure 3: Structural Model



Source: Own Work

(* p-value < 0.10; ** p-value < 0.05; *** p-value < 0.01)

To evaluate the model presented in Figure 3, in order to understand the moderator effect, we used the adjusted R2 since it is more robust to compare different models, since it does not rely on, nor it is affected by the number of used variables. As presented in Table 8, the second model, which uses trust as a moderator, has a greater explicative power to the usage intention and the outcomes presented by it, strengthening the belief that trust plays a significant role to understand the user and its intentions.

Table 8: Moderation Tests

Connections	Model 1 Coefficients	Model 2 (with moderators) Coefficients
AGE -> II	-0.075	-0.085
AGE -> UI	-0.015	-0.003
AGE -> W	0.058	0.022
C -> gamification	0.413***	0.413***
EMP -> UI	0.248***	0.126*
ENJ -> gamification	0.67***	0.67***

To be continued

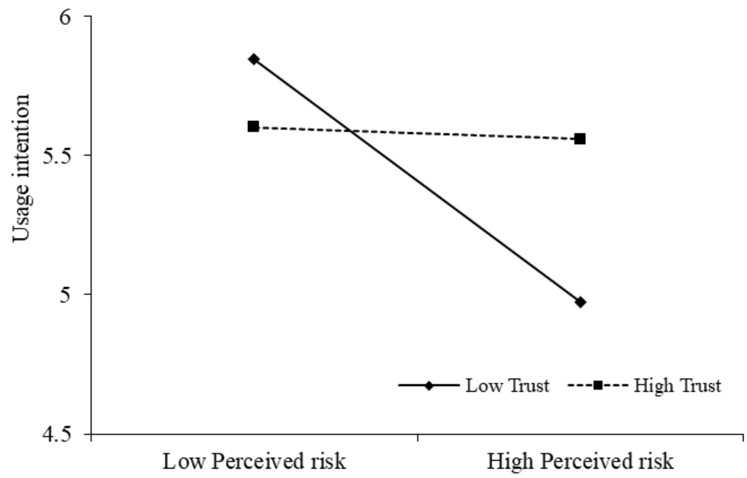
Table 8: Moderation Tests (cont.)

Connections	Model 1 Coefficients	Model 2 (with moderators) Coefficients
GENDER -> II	-0.017	-0.025
GENDER -> UI	-0.061	-0.047
GENDER -> W	0.056	0.029
P -> UI	0	-0.10
PR -> UI	-0.122***	-0.229***
INCOME -> II	-0.101*	-0.082*
INCOME -> UI	0.058	0.019
INCOME -> W	-0.105	-0.039
U -> UI	0.046	0.157**
UI -> II	0.838***	0.652***
UI -> W	0.766***	0.502***
gamification -> UI	0.584***	0.483***
T -> II		0.195***
T -> UI		0.085
T -> W		0.409***
T x gamification -> UI		0.126
T x P -> UI		-0.094
T x UI -> II		-0.048**
T x UI -> W		0.022
T x PR -> UI		0.207***
T x U -> UI		0.061
T x EMP -> UI		-0.126**
Adjusted R2 UI	77.0%	82.0%
Adjusted R2 II	72.8%	75.5%
Adjusted R2 W	57.1%	64.3%

Source: Own Work

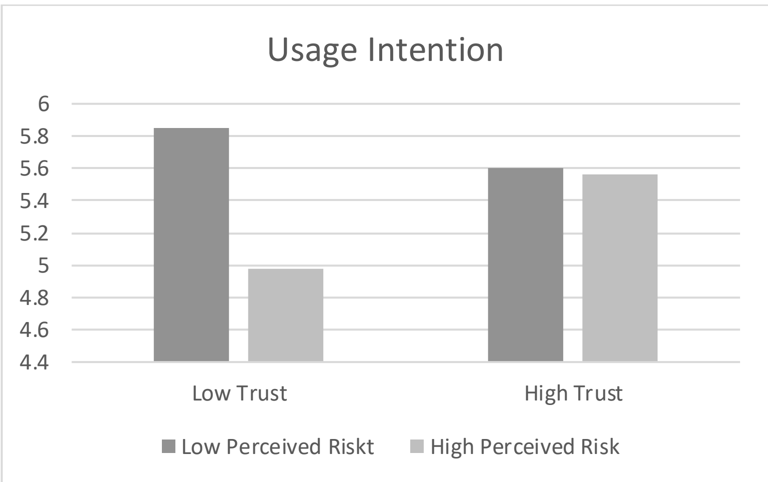
C – Challenge; Emp – Empowerment; Enj – Enjoyment; II – Individual Impact; P – Privacy; PR – Perceived Risk; T – Trust; U – Ubiquity; UI – Usage Intention; W – Wellbeing;

Figure 4: Trust moderator effect to Perceived Risk (Line view)



Source: Own Work

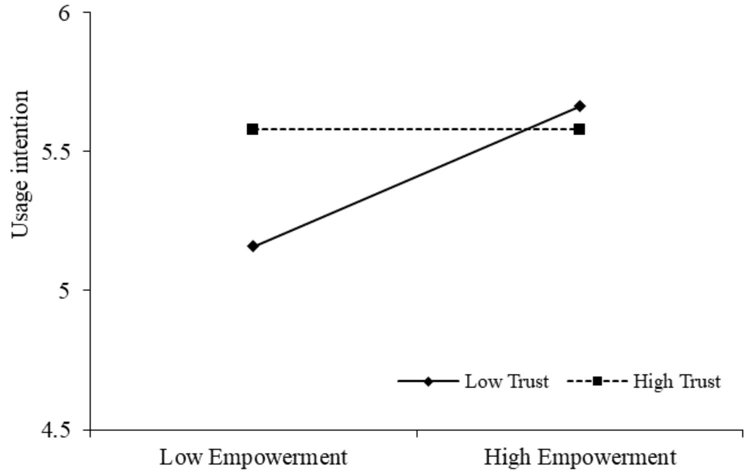
Figure 5: Trust Moderator effect to Perceived Risk (Bar view)



Source: Own Work

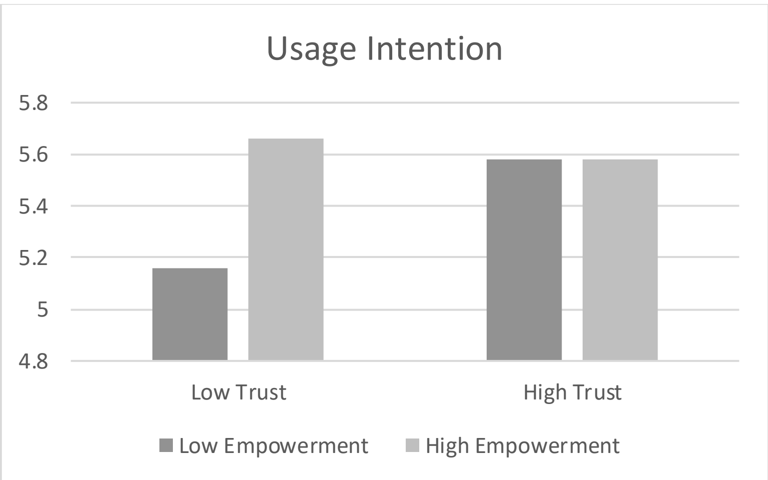
In Figure 4 and 5, consumers who present high levels of trust will still intend to use the technology even if perceived to be highly risky. However, for low levels of trust usage intention decreases as the perceived risk increases.

Figure 6: Trust moderator effect to Empowerment (Line view)



Source: Own Work

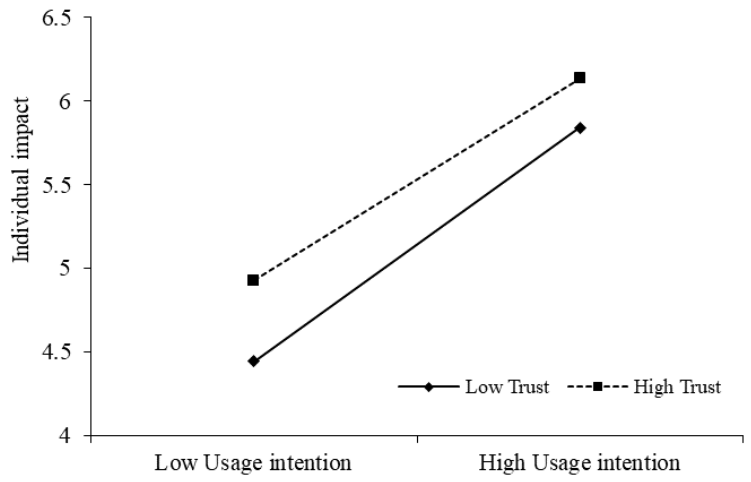
Figure 7: Trust moderator effect to Empowerment (Bar view)



Source: Own Work

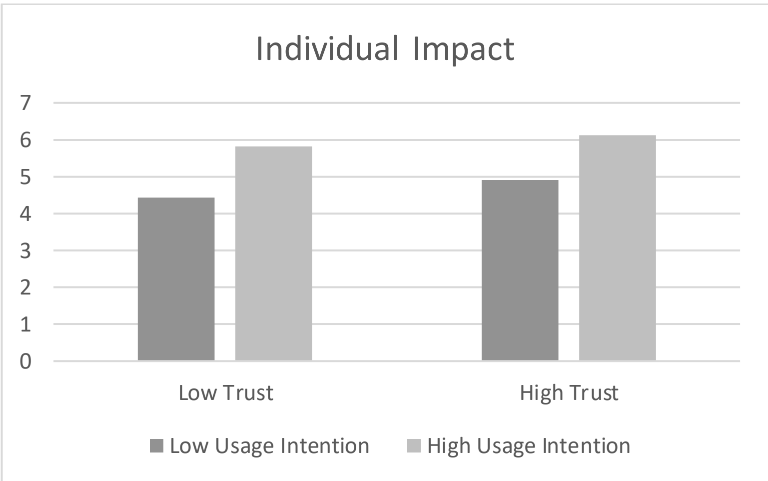
In Figure 6 and 7, higher empowerment drives a higher intention to use the technologies. However, when the consumer trust in technology increases, even if the perceived empowerment is low, the usage intention remains high.

Figure 8: Trust moderator effect to Usage Intention (Line View)



Source: Own Work

Figure 9: Trust moderator effect to Usage Intention (Bar view)



Source: Own Work

In Figure 8 and 9, for highly trusting consumers the individual impact is overall perceived as greater when compared to non-trusting individuals.

6 DISCUSSION

As we move forward into new technological eras, evolve into web 3.0, and create more robust and capable Artificial Intelligence which has increased power and a broader reach into our daily and private lives, it is important to understand the user willingness to be a part of these systems and to adopt them as a way to create a snowball effect, in which each user boosts these systems capability, and consequently, the increased capacity will bring more users (Grundner & Neuhofer, 2021).

Looking into the drivers of usage intention, our results confirm all hypotheses. Thus, this suggests the need for technology to be accessible anywhere at any time through its ubiquitous qualities, allowing the. users to be connected to the systems, avoiding situations of powerlessness when they cannot be connected to the system. This possible feeling of powerlessness is connected to the empowerment need to adhere to these systems and to accept them. The users tend to be more willing to accept the technologies whenever they feel that the power of decision and action is on their side, and they can better perform their daily life tasks, leading to a feeling of accomplishment. Lastly, given the smartness/intelligence of the smart city systems, the inclusion of game features reveals to be very important, leading not only the a more easy but also more enjoyable experience (Foster & Warwick, 2018). With this in mind, it is important to remove some mechanization of the system and introduce a more playable interface to them. The result from our study suggests that whenever the focus of these technologies is to give the user the ability to reach further and to have more power with easy and fun access, it will make them more driven into adhering to these systems.

Regarding the barriers to usage intention, perceived risk is the only negative factor that plays a key role in deterring the consumer from smart city systems that rely on artificial intelligence. From our research, we can understand that the users' primary fears rely on the possibility of committing a human error which could be exploited by a third party, or even on the ability of the systems to contain any flaws that might happen and would lead to some sort of harm to the consumer. This makes them view the technology as risky and as a way to lose control or power, and be more vulnerable (Elian, 2022; Shuhaiber & Mashal, 2019). From our model, we can see that the fear or perception of risk by the consumer has an even greater power to hinder them from the systems than the power they feel the systems might give them. On the other side, we understand that privacy is no longer a barrier to the consumer, the fear of losing sensitive information or that the platform might have security flaws creating this concern (Arpaci et al., 2015), doesn’t apply any longer and by the research, we can see that in what regards European and more precisely the Portuguese market, privacy is not something consumers are focused on. Overall, this can be explained by the enforcement of General Data Protection Regulations (GDPR) on the European market and that companies and even governmental agencies are compliant in enforcing data protection of the consumer even when using AI systems (Hamon et al., 2022).

From our research, the proposed outcomes are both strongly confirmed. Consumers feel that they have a greater impact as individuals on society when using these technologies. It is possible to verify that the weight of these technologies in improving or facilitating consumers' daily life and job has a high meaning to the user. Results also suggest that the use of these systems can positively contribute to the user's satisfaction, their needs, and overall quality of life.

Finally, the impact of trust in consumer decision-making needed to be taken into account for this study, as users have a huge leaning to view technology as risky. Therefore the large way to mitigate this tendency is by allowing the user to have greater trust and confidence in the system they are using (Arfi et al., 2021). Results suggest that the trust moderator effect is the highest when regarding perceived risk as a barrier. Thus, as presented in Figure 4 and 5, consumers who present high levels of trust will still intend to use the technology even if perceived to be highly risky. This undoubtedly means that trust mitigates the negative impact of the perceived risk. Therefore, it is important to create strategies, like demonstrations, discussions, forums, strategies, marketing plans, etc. that improve people's trust in the system.

Furthermore, based on users' trust they can feel more empowered and driven into using technology in their daily lives (Habib et al., 2020). As shown in Figure 6 and 7, higher empowerment drives a higher intention to use the technologies. However, when the consumer trusts in the technology, even if the perceived empowerment is low, they would still intend to use these systems.

In the same way, when the user trusts in the system they feel that their impact through it is greater, as proven by our research, meaning that for highly trusting consumers the individual impact is perceived as greater, as shown in Figure 8 and 9, supporting the need to create a trusty consumer base to the technology adoption.

6.1 Theoretical Implications

By following a belief-action-outcome framework, we create an understanding of behavioral drivers and especially outcomes of the usage intention, which was not extensively done in previous research, as studies beyond adoption are still scarce (Sarker et al., 2019). With this in mind, this study intends to increase awareness of the impact of technology adoption, since the main focus of the literature was based only on the antecedents rather than trying to understand what the usage intention brings to consumers. Furthermore, we divided the antecedents of this study into drivers and barriers according to Cenfetelli & Schwarz (2011), allowing us to have a better understanding of how some constructs affect consumer perception and intention towards technology usage. Finally, we believe that human behavior is complex and therefore several factors, like trust, can dictate how relationships work.

6.2 Practical Implictions

Regarding practical implications, this model can help to better implement these technologies and how to betters focus on the consumer allowing for eye-catching features and related marketing to be directed to the desired consumer group by understanding user perceptions. With this in mind, smart city systems must be available easily and in any given place, be user-friendly and playful, and provide users with active feedback to give them a feeling of power and impact and improve their wellbeing in the meantime. Meanwhile, we could focus on providing clear support and how we tackle possible risks associated with the technology so users are more confident and less fearful of experimenting. Given this, it is extremely important to increase consumers' trust in technology, since this can boost both the drivers and outcomes, and mitigate the barriers.

7 CONCLUSION

The adoption of technology, particularly smart city systems, and artificial intelligence has been a hot topic in recent years, both as means to understand how to better focus technologies on the market as well as trying to get citizens to use them and understand why some approaches may fail. Therefore, this work allows the identification of drivers and barriers to the usage intention of these systems. Regarding the drivers, empowerment, ubiquity, and gamification were found as relevant. On the other side, perceived risk was found as a barrier. It is therefore relevant for manufacturers, organizations, and municipalities to boost the drivers and try to minimize the barriers. If all this is managed correctly, then it will be possible to give consumers a better user experience and provide them with the necessary security measures while using the technology. This study allowed us to understand that feelings of power and impact are necessary to pull new consumers in, but also a friendly experience that provides wellbeing. Additionally, the negative impact of technology-perceived risks and user error was also identified, however, if well tackled and consumer trust is increased, then this effect can be mitigated. Given this, we found trust to have a significant role in dictating how the relationships between antecedents and use intention work.

8 RECOMMENDATIONS TO FUTURE WORK

This study is focused on the perception of artificial intelligence within the smart city context, this way it is being excluded from the perspective of the implications of smart domestic environments like smart homes, smart assistants, autonomous vehicles, etc. For further research would be important to understand how AI could impact on a smaller scale and what are the implications when it is used in a more private environment. Studies could also focus on trying to get interviews with respondents, specifically consumers, to understand their perception of more humanistic and in-depth research of human intentions behind adoption. Lastly, despite the set of variables used in this research it is possible to verify through the literature that for an exploratory study the chosen set is not restrictive, and other variables presented could be used based on the desired context.

REFERENCE LIST

1. Abduljabbar, R., Dia, H., Liyanage, S., & Bagloee, S. A. (2019). Applications of Artificial Intelligence in Transport: An Overview. *Sustainability*, *11*(1), 1–24. https://doi.org/10.3390/su11010189

2. Abid, N., Marchesani, F., Ceci, F., Masciarelli, F., & Ahmad, F. (2022a). Cities trajectories in the digital era: Exploring the impact of technological advancement and institutional quality on environmental and social sustainability. *Journal of Cleaner Production*, *377*(April), 134378. https://doi.org/10.1016/j.jclepro.2022.134378

3. Abid, N., Marchesani, F., Ceci, F., Masciarelli, F., & Ahmad, F. (2022b). Cities trajectories in the digital era: Exploring the impact of technological advancement and institutional quality on environmental and social sustainability. *Journal of Cleaner Production*, *377*(2), 134378. https://doi.org/10.1016/j.jclepro.2022.134378

4. Acheampong, R. A., Cugurullo, F., Gueriau, M., & Dusparic, I. (2021). Can autonomous vehicles enable sustainable mobility in future cities? Insights and policy challenges from user preferences over different urban transport options. *Cities*, *112*(February), 103134. https://doi.org/10.1016/j.cities.2021.103134

5. Alam, T. (2021). Cloud-Based IoT Applications and Their Roles in Smart Cities. *Smart Cities*, *4*(3), 1196–1219. https://doi.org/10.3390/smartcities4030064

6. Ali, T., Irfan, M., Alwadie, A. S., & Glowacz, A. (2020). IoT-Based Smart Waste Bin Monitoring and Municipal Solid Waste Management System for Smart Cities. *Arabian Journal for Science and Engineering*, *45*(12), 10185–10198. https://doi.org/10.1007/s13369-020-04637-w

7. Alsamhi, S., Ma, O., Ansari, M., & Gupta, S. (2019). Collaboration of Drone and Internet of Public Safety Things in Smart Cities: An Overview of QoS and Network Performance Optimization. *Drones*, *3*(1), 13. https://doi.org/10.3390/drones3010013

8. Angelidou, M. (2015). Smart cities: A conjuncture of four forces. *Cities*, *47*, 95–106. https://doi.org/10.1016/j.cities.2015.05.004

9. Aparicio, M., Oliveira, T., Bacao, F., & Painho, M. (2019). Gamification: A key determinant of massive open online course (MOOC) success. *Information & Management*, *56*(1), 39–54. https://doi.org/10.1016/j.im.2018.06.003

10. Arfi, W. Ben, Nasr, I. Ben, Kondrateva, G., & Hikkerova, L. (2021). The role of trust in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context. *Technological Forecasting and Social Change*, *167*(February), 120688. https://doi.org/10.1016/j.techfore.2021.120688

11. Arpaci, I., Kilicer, K., & Bardakci, S. (2015). Effects of security and privacy concerns on educational use of cloud services. *Computers in Human Behavior*, *45*, 93–98. https://doi.org/10.1016/j.chb.2014.11.075

12. Bakıcı, T., Almirall, E., & Wareham, J. (2013). A Smart City Initiative: the Case of Barcelona. *Journal of the Knowledge Economy*, *4*(2), 135–148. https://doi.org/10.1007/s13132-012-0084-9

13. Balakrishnan, J., Dwivedi, Y. K., Hughes, L., & Boy, F. (2021). Enablers and Inhibitors of AI-Powered Voice Assistants: A Dual-Factor Approach by Integrating the Status Quo Bias and Technology Acceptance Model. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-021-10203-y

14. Baptista, G., & Oliveira, T. (2019). Gamification and serious games: A literature meta-analysis and integrative model. *Computers in Human Behavior*, *92*(May 2018), 306–315. https://doi.org/10.1016/j.chb.2018.11.030

15. Burry, M. (2022). A new agenda for AI-based urban design and planning. In I. As, P. Basu, & P. Talwar (Eds.), *Artificial Intelligence in Urban Planning and Design* (pp. 3–20). Elsevier. https://doi.org/10.1016/B978-0-12-823941-4.00005-6

16. Cenfetelli, R. T., & Schwarz, A. (2011). Identifying and Testing the Inhibitors of Technology Usage Intentions. *Information Systems Research*, *22*(4), 808–823. https://doi.org/10.1287/isre.1100.0295

17. Chaudhari, M. S., Patil, B., & Raut, V. (2019). IoT based Waste Collection Management System for Smart Cities: An Overview. *2019 3rd International Conference on Computing Methodologies and Communication (ICCMC)*, *Iccmc*, 802–805. https://doi.org/10.1109/ICCMC.2019.8819776

18. Chin, W. W. (1998). Issues and Opinion on Structural Equation Modeling. *MIS Quarterly*, *22*(1), 7–16. http://www.jstor.org/stable/249674

19. Choi, J. (2022). Enablers and inhibitors of smart city service adoption: A dual-factor approach based on the technology acceptance model. *Telematics and Informatics*, *75*(October), 101911. https://doi.org/10.1016/j.tele.2022.101911

20. Davis, F. D. (1986). *A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results*. Massachusetts Institute of Technology.

21. de Castro Neto, M., & Rego, J. S. (2019). Urban Intelligence for Sustainability. In *Lecture Notes in Information Systems and Organisation* (Vol. 31, pp. 139–159). https://doi.org/10.1007/978-3-030-14850-8_10

22. Dhillon, G., Oliveira, T., Susarapu, S., & Caldeira, M. (2016). Deciding between information security and usability: Developing value based objectives. *Computers in Human Behavior*, *61*, 656–666. https://doi.org/10.1016/j.chb.2016.03.068

23. Dimitrakopoulos, G., Uden, L., & Varlamis, I. (2020). The Future of Intelligent Transport Systems. In *The Future of Intelligent Transport Systems*. Elsevier. https://doi.org/10.1016/C2018-0-02715-2

24. El-Haddadeh, R., Weerakkody, V., Osmani, M., Thakker, D., & Kapoor, K. K. (2019). Examining citizens' perceived value of internet of things technologies in facilitating public sector services engagement. *Government Information Quarterly*, *36*(2), 310–320. https://doi.org/10.1016/j.giq.2018.09.009

25. El Barachi, M., Salim, T. A., Nyadzayo, M. W., Mathew, S., Badewi, A., & Amankwah-Amoah, J. (2022). The relationship between citizen readiness and the intention to continuously use smart city services: Mediating effects of satisfaction and discomfort. *Technology in Society*, *71*(August), 102115. https://doi.org/10.1016/j.techsoc.2022.102115

26. El Hedhli, K., Chebat, J.-C., & Sirgy, M. J. (2013). Shopping well-being at the mall: Construct, antecedents, and consequences. *Journal of Business Research*, *66*(7), 856–863. https://doi.org/10.1016/j.jbusres.2011.06.011

27. Elian, A. A. (2022). Hey Google: Does Environmental Beliefs and Perceived Privacy Risk Influence Potential User's Intention to Use a Smart Home System in Indonesia? *Smart City*, *2*(1). https://doi.org/10.56940/sc.v2.i1.5

28. Flavián, C., & Guinalíu, M. (2006). Consumer trust, perceived security and privacy policy. *Industrial Management & Data Systems*, *106*(5), 601–620. https://doi.org/10.1108/02635570610666403

29. Fornell, C., & Bookstein, F. L. (1982). Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-Voice Theory. *Journal of Marketing Research*, *19*(4), 440. https://doi.org/10.2307/3151718

30. Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

31. Foster, T., & Warwick, S. (2018). Nostalgia, gamification and staff development – moving staff training away from didactic delivery. *Research in Learning Technology*, *26*(1063519), 1–14. https://doi.org/10.25304/rlt.v26.2021

32. Füller, J., Mühlbacher, H., Matzler, K., & Jawecki, G. (2009). Consumer Empowerment Through Internet-Based Co-creation. *Journal of Management Information Systems*, *26*(3), 71–102. https://doi.org/10.2753/MIS0742-1222260303

33. Gansser, O. A., & Reich, C. S. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society*, *65*, 101535. https://doi.org/10.1016/j.techsoc.2021.101535

34. Giffinger, R., Fertner, C., Kramar, H., & Meijers, E. (2007). City-ranking of European Medium-Sized Cities. In *Digital Agenda for Europe*.

35. Grundner, L., & Neuhofer, B. (2021). The bright and dark sides of artificial intelligence: A futures perspective on tourist destination experiences. *Journal of Destination Marketing & Management*, *19*(July 2020), 100511. https://doi.org/10.1016/j.jdmm.2020.100511

36. Guillen-Royo, M. (2019). Sustainable consumption and wellbeing: Does on-line shopping matter? *Journal of Cleaner Production*, *229*, 1112–1124. https://doi.org/10.1016/j.jclepro.2019.05.061

37. Habib, A., Alsmadi, D., & Prybutok, V. R. (2020). Factors that determine residents' acceptance of smart city technologies. *Behaviour & Information Technology*, *39*(6), 610–623. https://doi.org/10.1080/0144929X.2019.1693629

38. Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414–433. https://doi.org/10.1007/s11747-011-0261-6

39. Hamon, R., Junklewitz, H., Sanchez, I., Malgieri, G., & De Hert, P. (2022). Bridging the Gap Between AI and Explainability in the GDPR: Towards Trustworthiness-by-Design in Automated Decision-Making. *IEEE Computational Intelligence Magazine*, *17*(1), 72–85. https://doi.org/10.1109/MCI.2021.3129960

40. Herzberg, F., Mausner, B., & Snyderman, B. B. (2017). *The motivation to work* (Routledge (ed.)). Transaction Publishers.

41. Huang, D., Wang, S., & Liu, Z. (2021). A systematic review of prediction methods for emergency management. *International Journal of Disaster Risk Reduction*, *62*(November 2020), 102412. https://doi.org/10.1016/j.ijdrr.2021.102412

42. IEA. (2023). *Electricity*. https://www.iea.org/fuels-and-technologies/electricity

43. Johnson, R. E., Rosen, C. C., & Djurdjevic, E. (2011). Assessing the impact of common method variance on higher order multidimensional constructs. *Journal of Applied Psychology*, *96*(4), 744–761. https://doi.org/10.1037/a0021504

44. Ke, W., Liu, H., Wei, K. K., Gu, J., & Chen, H. (2009). How do mediated and non-mediated power affect electronic supply chain management system adoption? The mediating effects of trust and institutional pressures. *Decision Support Systems*, *46*(4), 839–851. https://doi.org/10.1016/j.dss.2008.11.008

45. Khatoun, R., & Zeadally, S. (2016). Smart cities. *Communications of the ACM*, *59*(8), 46–57. https://doi.org/10.1145/2858789

46. Koumetio Tekouabou, S. C., Diop, E. B., Azmi, R., & Chenal, J. (2023). Artificial Intelligence Based Methods for Smart and Sustainable Urban Planning: A Systematic Survey. *Archives of Computational Methods in Engineering*, *30*(2), 1421–1438. https://doi.org/10.1007/s11831-022-09844-2

47. Lin, T.-C., Huang, S.-L., & Hsu, C.-J. (2015). A dual-factor model of loyalty to IT product – The case of smartphones. *International Journal of Information Management*, *35*(2), 215–228. https://doi.org/10.1016/j.ijinfomgt.2015.01.001

48. Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology*, *86*(1), 114–121. https://doi.org/10.1037/0021-9010.86.1.114

49. Manville, C., Cochrane, G., Cave, J., Millard, J., Penderson, J., Thaarup, R., Liebe, A., Wissner, M., Massnik, R., & Kotterink, B. (2014). Mapping Smart Cities in the EU. In *Directorate General for Internal Policies*.

50. Mariani, M. M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation*, *122*(December 2021), 102623. https://doi.org/10.1016/j.technovation.2022.102623

51. Marsal-Llacuna, M.-L., Colomer-Llinàs, J., & Meléndez-Frigola, J. (2015). Lessons in urban monitoring taken from sustainable and livable cities to better address the Smart Cities initiative. *Technological Forecasting and Social Change*, *90*(PB), 611–622. https://doi.org/10.1016/j.techfore.2014.01.012

52. Melville. (2010). Information Systems Innovation for Environmental Sustainability. *MIS Quarterly*, *34*(1), 1. https://doi.org/10.2307/20721412

53. Neves, C., & Oliveira, T. (2023). Drivers and Outcomes of Sustainable Technologies: A Mixed-Methods Study of 4 EU Countries. *Thirty-First European Conference on Information Systems (ECIS 2023)*, 1–11.

54. Nikitas, A., Michalakopoulou, K., Njoya, E. T., & Karampatzakis, D. (2020). Artificial Intelligence, Transport and the Smart City: Definitions and Dimensions of a New Mobility Era. *Sustainability*, *12*(7), 2789. https://doi.org/10.3390/su12072789

55. Ozkan, S., & Kanat, I. E. (2011). e-Government adoption model based on theory of planned behavior: Empirical validation. *Government Information Quarterly*, *28*(4), 503–513. https://doi.org/10.1016/j.giq.2010.10.007

56. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

57. Porter, C. E., & Donthu, N. (2008). Cultivating Trust and Harvesting Value in Virtual Communities. *Management Science*, *54*(1), 113–128. https://doi.org/10.1287/mnsc.1070.0765

58. Rodrigues, C. F. (2023). *Portugal Desigual | Um retrato das desigualdades de rendimentos e da pobreza no país*. https://www.ffms.pt/pt-pt/estudos/portugal-desigual-um-retrato-das-desigualdades-de-rendimentos-e-da-pobreza-no-pais

59. Rojek, I., & Studzinski, J. (2019). Detection and Localization of Water Leaks in Water Nets Supported by an ICT System with Artificial Intelligence Methods as a Way Forward for Smart Cities. *Sustainability*, *11*(2), 518. https://doi.org/10.3390/su11020518

60. Sarker, S., Chatterjee, S., Xiao, X., & Elbanna, A. (2019). The Sociotechnical Axis of Cohesion for the IS Discipline: Its Historical Legacy. *MIS Quarterly*, *43*(3), 1–5.

61. Serban, A. C., & Lytras, M. D. (2020). Artificial Intelligence for Smart Renewable Energy Sector in Europe—Smart Energy Infrastructures for Next Generation Smart Cities. *IEEE Access*, *8*, 77364–77377. https://doi.org/10.1109/ACCESS.2020.2990123

62. Shuhaiber, A., & Mashal, I. (2019). Understanding users' acceptance of smart homes. *Technology in Society*, *58*(March 2018), 101110. https://doi.org/10.1016/j.techsoc.2019.01.003

63. Tulumello, S., & Iapaolo, F. (2022). Policing the future, disrupting urban policy today. Predictive policing, smart city, and urban policy in Memphis (TN). *Urban Geography*, *43*(3), 448–469. https://doi.org/10.1080/02723638.2021.1887634

64. Ullah, N., Al-Rahmi, W. M., Alfarraj, O., Alalwan, N., Alzahrani, A. I., Ramayah, T., & Kumar, V. (2022). Hybridizing cost saving with trust for blockchain

technology adoption by financial institutions. *Telematics and Informatics Reports*, *6*(April), 100008. https://doi.org/10.1016/j.teler.2022.100008

65. Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

66. Wilson, C., Hargreaves, T., & Hauxwell-Baldwin, R. (2015). Smart homes and their users: a systematic analysis and key challenges. *Personal and Ubiquitous Computing*, *19*(2), 463–476. https://doi.org/10.1007/s00779-014-0813-0

67. Yang, H., & Lee, H. (2023). Smart city and remote services: The case of South Korea's national pilot smart cities. *Telematics and Informatics*, *79*(August 2022), 101957. https://doi.org/10.1016/j.tele.2023.101957

68. Yigitcanlar, T., Kankanamge, N., Regona, M., Ruiz Maldonado, A., Rowan, B., Ryu, A., Desouza, K. C., Corchado, J. M., Mehmood, R., & Li, R. Y. M. (2020). Artificial Intelligence Technologies and Related Urban Planning and Development Concepts: How Are They Perceived and Utilized in Australia? *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(4), 187. https://doi.org/10.3390/joitmc6040187

69. Zannat, K. E., & Choudhury, C. F. (2019). Emerging Big Data Sources for Public Transport Planning: A Systematic Review on Current State of Art and Future Research Directions. *Journal of the Indian Institute of Science*, *99*(4), 601–619. https://doi.org/10.1007/s41745-019-00125-9

70. Zhang, N., Hwang, B.-G., Lu, Y., & Ngo, J. (2022). A Behavior theory integrated ANN analytical approach for understanding households adoption decisions of residential photovoltaic (RPV) system. *Technology in Society*, *70*(April), 102062. https://doi.org/10.1016/j.techsoc.2022.102062

71. Zhu, W., Yan, R., & Song, Y. (2022). Analysing the impact of smart city service quality on citizen engagement in a public emergency. *Cities*, *120*(1), 103439. https://doi.org/10.1016/j.cities.2021.103439

APPENDICES

Appendix 1: Povzetek (Summary in Slovene language)

Ta raziskava se osredotoča na razumevanje, kaj uporabnike spodbuja k sprejemanju pametnih mestnih sistemov, zlasti tistih, ki vključujejo umetno inteligenco kot glavno gonilo, in kakšne rezultate lahko iz tega potegnemo. Proučeval sem, kako sprejemanje tehnologije vpliva na življenje potrošnikov. Predhodnike sem razdelil na gonilnike in ovire za namero uporabe ter preučil, kako vplivajo na vedenjske rezultate. Moj model je bil preizkušen z raziskavo, v kateri je sodelovalo 211 portugalskih potrošnikov. Uporabil sem tehniko modeliranja strukturnih enačb in pokazal, da imajo konstrukti občutek moči, uporabniška izkušnja in dostopnost pomembno vlogo pri sprejemanju pametnih mestnih sistemov. Zaznana tveganja, povezana s sistemi pametnih mest, so ovirala sprejetje. Nazadnje, namera uporabe pozitivno vpliva na počutje in učinkovitost v vsakdanjem življenju.

Appendix 2: Survey

Consent

This questionnaire intends to evaluate the citizens' motivations to use smart city systems containing artificial intelligence.

Your participation is voluntary and much appreciated. All the responses are anonymous.

The questionnaire takes approximately 6 minutes.

If you have any questions, please contact joaopedrovinagre97@gmail.com. If you are 18 years old or older and agree to participate, please click on the box.

Introduction

Introduction **Smart city systems** refer to the use of technology and data analysis to improve the **efficiency, sustainability, safety, and quality of life** in urban areas. These systems utilize a network of sensors, devices, and analytic tools to collect and analyze data from various sources such as transportation systems, public safety systems, energy grids, and public infrastructure. The use of Artificial Intelligence in Smart Cities has the potential to make urban areas more efficient and sustainable, while also improving public safety and enhancing the quality of life. Some examples of Artificial Intelligence use in Smart Cities are:

- **Intelligent Transportation Systems:** AI can analyze real-time data from traffic sensors and cameras to adjust traffic signals and provide drivers with alternative routes to avoid congestion.
- **Public Safety:** AI-powered video analytics systems can detect and identify suspicious activities in public spaces and alert law enforcement agencies.
- **Energy Management:** AI can analyze data from smart meters to predict energy usage patterns and adjust energy supply.
- **Waste Management:** AI can analyze data from sensors in trash cans to predict when they will be full and schedule pickups.
- **Water Management:** AI can analyze data from sensors in water distribution systems to detect leaks and reduce water loss.

Citizen Engagement

From the examples below, which applications have you used or had contact with? (Multiple choice)

Transit apps; Ride sharing apps; Parking apps; Bike sharing; Smart meters; Surveillance or emergency alert apps; Civic participation apps; Air quality apps; Green initiative apps; others;

Trust based on (Arfi et al., 2021; Ullah et al., 2022)

Concerning my perception of these systems. (1 – Strongly disagree; 7 – Strongly agree)

T1. I trust in the technology Smart Cities Systems containing Artificial Intelligence are using.

T2. I trust in the ability of Smart Cities Systems containing Artificial Intelligence to protect my privacy.

T3. Using Smart Cities Systems containing Artificial Intelligence is financially secure.

T4. I am not worried about the security of Smart Cities Services containing Artificial Intelligence

Perceived risk based on (Arfi et al., 2021)

Referring to possible risks. (1 – Strongly disagree; 7 – Strongly agree)

PR1. Using Smart Cities Systems containing Artificial Intelligence seems risky.

PR2. I feel that using Smart Cities Systems containing Artificial Intelligence would cause me a lot of trouble if something went wrong.

PR3. Basically, I'm sure I would make a mistake if I used Smart Cities Systems containing Artificial Intelligence.

Privacy based on (El-Haddadeh et al., 2019; Gansser & Reich, 2021)

Regarding the use of your data. (1 – Strongly disagree; 7 – Strongly agree)

P1. Smart Cities Systems containing Artificial Intelligence should not sell my personal information to other companies.

P2. Smart Cities Systems containing Artificial Intelligence should not share my personal information with other companies unless I am specifically authorized to do so.

P3. Smart Cities Systems containing Artificial Intelligence should not use my personal information for any purpose not specifically authorized by me.

Empowerment based on (El-Haddadeh et al. 2019)

Regarding your perception of Smart city systems. (1 – Strongly disagree; 7 – Strongly agree)

Emp1. I feel enthused to actively use Smart Cities Systems containing Artificial Intelligence.

Emp2. Using Smart Cities Systems containing Artificial Intelligence would give me a feeling of accomplishment.

Emp3. With the use of Smart Cities Systems containing Artificial Intelligence, I am able to manage my everyday life activities better.

Ubiquity based on (Yang & Lee, 2023)

Regarding your perception of Smart city systems. (1 – Strongly disagree; 7 – Strongly agree)

U1. I should be able to access Smart Cities Systems containing Artificial Intelligence through mobile devices, wearables, transportation, kiosks, and other various devices.

U2. It should be convenient to use Smart Cities Systems containing Artificial Intelligence while moving from place to place or when doing anything else.

U3. Ubiquity is an outstanding advantage of Smart Cities Systems containing Artificial Intelligence.

Enjoyment based on (Aparicio et al., 2019)

Regarding your perception of Smart city systems. (1 – Strongly disagree; 7 – Strongly agree)

Enj1. I find using Smart Cities Systems containing Artificial Intelligence to be enjoyable.

Enj2. The process of using Smart Cities Systems containing Artificial Intelligence seems pleasant.

Enj3. I should have fun using Smart Cities Systems containing Artificial Intelligence.

Challenge based on (Aparicio et al., 2019)

Regarding your perception of Smart city systems. (1 – Strongly disagree; 7 – Strongly agree)

C1. The Smart Cities Systems containing Artificial Intelligence should provide "hints" in text that helps me overcome the challenges.

C2. The Smart Cities Systems containing Artificial Intelligence should provide "online support" that helps me overcome the challenges.

C3. The Smart Cities Systems containing Artificial Intelligence should provide video or audio auxiliaries that help me overcome the challenges.

Usage Intention based on (Yang & Lee, 2023)

Regarding your perception of Smart city systems. (1 – Strongly disagree; 7 – Strongly agree)

UI1. I intend to use Smart Cities Systems containing Artificial Intelligence in the future.

UI2. I predict I would use Smart Cities Systems containing Artificial Intelligence in the future.

UI3. I would recommend others to use Smart Cities Systems containing Artificial Intelligence.

Well-being based on (El Hedhli et al., 2013)

Regarding your perception of Smart city systems. (1 – Strongly disagree; 7 – Strongly agree)

W1. Smart Cities Systems containing Artificial Intelligence satisfy my overall needs.

W2. Smart Cities Systems containing Artificial Intelligence play a very important role in my social well-being.

W3. Smart Cities Systems containing Artificial Intelligence play a very important role in my leisure well-being.

W4. Smart Cities Systems containing Artificial Intelligence play an important role in enhancing my quality of life.

Individual Impact based on (Aparicio et al., 2019)

Regarding your perception of Smart city systems. (1 – Strongly disagree; 7 – Strongly agree)

II1. Smart Cities Systems containing Artificial Intelligence enables me to accomplish tasks more quickly.

II2. The use of Smart Cities Systems containing Artificial Intelligence could increase my productivity.

II3. The use of Smart Cities Systems containing Artificial Intelligence could make it easier to accomplish tasks.

II4. The use of Smart Cities Systems containing Artificial Intelligence could be useful for my job.

Appendix 3: Ethics Comittee Aproval Certificate

NOVA IMS Information Management School

This is to certify that

Project No.: **INFSYS2023-5-153815**

Project Title: **Master thesis**

Principal Researcher: **Joao Santos**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 5/15/2023.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 5/15/2023

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt