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Information Management School

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Mestrado em Gestão de Informação
Master Program in Information Management

Drivers of people's acceptance of Artificial Intelligence use in e-Government

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Dissertation presented as partial requirement for obtaining the Master's degree in Information Management

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DRIVERS OF PEOPLE'S ACCEPTANCE OF ARTIFICIAL INTELLIGENCE USE IN E-GOVERNMENT

by

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October 2022

ABSTRACT

The current advancement of information technologies has created the conditions to introduce and popularise e-government, bringing citizens closer to public administration. Yet, e-government faces challenges such as the digital divide, civic data overload, lack of trust in government institutions and their online services, and privacy and security concerns. Artificial intelligence has the potential to address many of those challenges. To successfully adopt such a disruptive technology, it is imperative to delve into the drivers leading to citizens' acceptance.

Therefore, this study proposes a theoretical model to explore and better understand the citizens' acceptance towards the use of AI in e-government. We used an online survey to collect data from Portuguese citizens (N = 208). The results reveal that the perceived usefulness and trust of AI and social influence significantly contribute to the acceptance of AI use in e-government. Political interest is only significant for women. Participants recognize the benefits of using AI but raise several fears, especially concerning the lack of trust in the government. Despite the majority being aware of AI and e-government, some are not or are not aware of how AI can be used in e-government. The findings of this study can help local and national governments assess the acceptance of the adoption of AI-based technologies in e-government and define tailored strategies to respond to citizens' concerns and highlight benefits to society.

KEYWORDS

Artificial Intelligence; e-Government; Acceptance of AI use; Features of the technology; Characteristics of individuals

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
AIA	Artificial Intelligence Awareness
AI HLEG	High-Level Expert Group on Artificial Intelligence
AIUEG	Acceptance of Artificial Intelligence Use in e-Government
CORDIS	Community Research and Development Information Service
CSIS	Center for Strategic and International Studies
EU	European Union
ICTs	Information and Communication Technologies
NLP	Natural Language Processing
OECD	Organisation for Economic Co-operation and Development
OSE	Online Self-Efficacy
PC	Privacy Concerns
PI	Political Interest
PUAI	Perceived Usefulness of Artificial Intelligence
SI	Social Influence
TAI	Trust in Artificial Intelligence
UNESCO	United Nations Educational, Scientific and Cultural Organization

1. INTRODUCTION

Currently, Artificial Intelligence (AI) empowers a constellation of mainstream technologies (Stone et al., 2015) that may reshape how we behave, work, cooperate, and even make decisions. The impact of societal and economic innovations created by these technologies is already noticeable in several industries, including financial services, healthcare, telecommunications, transportation, among others (Twentyman, 2018). Compared to the private sector, the public sector is lagging behind in AI adoption (Council of Europe, 2020). However, several governments in Europe are trying to catch up and close the current gap. As uncertainty increases and demands shift, governments have realised that it is crucial to innovate and incorporate new technologies to deliver better services to citizens (Berryhill et al., 2019). According to a study commissioned by Microsoft and conducted by EY, 65% of surveyed European public organisations have recognised the value of AI, seeing it as a priority, and 67% have adopted at least one AI application (EY & Microsoft, 2020).

In the coming years, mundane and repetitive tasks are expected to be executed by AI, allowing government officials to devote more time to creative, high-value work (Berryhill et al., 2019). Furthermore, AI-based technologies can enhance the quality of public services by improving their efficiency and responsiveness. For instance, guiding decision-making by summarising vast amounts of data and increasing citizen engagement by helping them be more informed about key policy issues (Berryhill et al., 2019; König & Wenzelburger, 2020). On the other hand, these technologies can also be used with malicious intentions by facilitating control over information and communication, spreading misinformation, reinforcing filter bubbles, and manipulating citizens (König & Wenzelburger, 2020; Savaget et al., 2019).

Although research on the adoption of AI in the public sector is gradually increasing (Fast & Horvitz, 2017), its implementation is still in an embryonic stage. One field in the public sector in which research on AI lacks development is e-government, which encompasses "*the use of information and communication technologies (ICTs), particularly the Internet, as a tool to achieve better government*" (OECD, 2003). Yet, this tool faces challenges such as the digital divide, civic data overload, lack of trust in government institutions and their online services, and privacy and security concerns (Al-Mushayt, 2019; Chen & Aitamurto, 2019; Le Blanc, 2020; Shahab et al., 2021). The integration of AI technologies may bring a significant contribution to overcome some of those challenges. Eventually, this integration can lead to reduced corruption, increased transparency, more inclusive and broader citizen participation, and implementation of better policies and government programs (Mohammed, 2018). To successfully adopt these technologies, it is vital to first explore and understand the drivers leading to citizens' acceptance. Therefore, the objective of this study includes exploring the extent to which some of the features of the technology itself and personal characteristics can influence the acceptance of AI use in e-government in Portugal. We propose a research model and conduct a survey to collect data on the general population.

This research proceeds as follows. First, we introduced the definition of e-government and its challenges, briefly discussed AI potential impact in e-government, and then proposed a research model and hypotheses. To evaluate the model, we used quantitative data collected from Portuguese citizens. Then, the results of quantitative and qualitative analyses are presented. We conclude with a discussion of the findings and their implications, and limitations and future research.

2. LITERATURE REVIEW

2.1. E-GOVERNMENT AND ITS CHALLENGES

Electronic government (e-government) is defined as governments' use of information and communication technologies (ICTs) in its structures and procedures, combined with organisational change (OECD, 2003), to (i) *improve public services and administrative efficiency*, (ii) *promote openness and transparency*, (iii) *encourage the participation of citizens and other stakeholders in decision-making*, (iv) *improve ethical behaviour and professionalism*, (v) *improve trust and confidence in government*, and (vi) *improve social value and well-being* (Twizeyimana & Andersson, 2019).

Despite being recognized as a powerful tool and adopted in several countries (United Nations, 2020), e-government alone does not guarantee better government responsiveness, citizen satisfaction, or increased citizen engagement and participation (Mishra & Geleta, 2020). Presently, it faces several challenges that must be addressed:

- ***Digital divide***: Low levels of digital literacy and inequality of access to ICTs may prevent some citizens from benefiting from the efficiency and diligence of digital government (Le Blanc, 2020);
- ***Civic data overload***: Despite decision-makers encouraging mass citizen participation and desiring to use their inputs and suggestions to make decisions, governments still lack the necessary tools and resources to process and analyse them effectively (Chen & Aitamurto, 2019). In addition, citizens exhibit difficulty accessing and comprehending government information available online (Toots, 2019). These limitations and difficulties decrease the prospect of a meaningful exchange of ideas and lead to a decline in the overall quality of mass participation (Arana-Catania et al., 2021);
- ***Trust in government institutions and their online services:*** Citizens' adoption and use of e-government primarily depend on their trust in government institutions and their online services. Unfortunately, many citizens complain about the lack of quality and effectiveness of public online services or, due to personal beliefs, still prefer traditional means of reaching public entities (Al-Mushayt, 2019; Le Blanc, 2020);
- ***Privacy and security concerns***: As a result of the increase of data leakage and misuse, systems intrusion and cyber incidents, citizens' concerns about privacy and security have also increased (Le Blanc, 2020).

2.2. AI POTENTIAL IMPACT IN E-GOVERNMENT

AI focuses on studying and constructing intelligent agents capable of perceiving and interpreting their surrounding environment, learning and improving, and deciding autonomously the right thing to do to achieve goals (AI HLEG, 2019; Kaplan & Haenlein, 2019; Mehr, 2017; Nilsson, 2009; Poole & Mackworth, 2017).

The integration of AI technologies may bring a significant contribution to overcome some of the current challenges of e-government. By exponentially increasing the power of ICTs (UNESCO, 2019), they can process massive amounts of data quickly and effectively, increase citizens' control over public administration by increasing transparency, allowing greater scrutiny of public activities and expenditures, and facilitating communication and collaboration between citizens and the government (Savaget et al., 2019). Additionally, they can be used to extract data from unstructured sources, such as public blogs and forums, and help policymakers outline public opinion on diverse issues to better plan and implement policies (Milano et al., 2014).

Recent literature explored whether natural language processing (NLP) and machine learning techniques can improve citizens' experience in participation platforms. The findings revealed that these techniques improved the effectiveness of participation processes significantly by reducing the time required to search for similar proposals, enabling tasks that previously were not viable, such as summarizing texts or the discovery of users with similar interests (Arana-Catania et al., 2021).

We identified some projects, funded by the EU's framework programmes for research and innovation and published in CORDIS (Community Research and Development Information Service), which aim to explore the benefits of adopting AI in e-government. Some of these projects, resulting from cooperation between public and private entities, are shown in table 2.

Table 1 – AI projects in e-Government

Project	**Focus of the project**	**Participants**
SIMplifying the interaction with Public Administration Through Information technology for Citizens and cOmpanies (**SIMPATICO**)	Approach to deliver personalised online services by combining AI-based technologies with the wisdom of the crowd, collected from explicit and implicit information from citizens, other stakeholders, and their user logs and past user interactions.	Italy, Spain, UK
KAROS	Smart mobility platform that promotes shared rides by combining AI-based technologies, mobile technologies and big data. It predicts users' trips over the next five days and matches them automatically with others with similar routes to unlock mobility in rural and suburban areas.	France
Smart Toolbox for Engaging Citizens into a People-Centric Observation Web (**SCENT**)	Set of collaborative technologies that enable citizens to become the "*eyes*" of the policymakers and local authorities by monitoring environmental change. It uses AI-based technologies to extract valuable information, which can be used to, for example, improve flood modelling.	Greece, Ireland, Israel, Italy, Netherlands, Romania
GAMMA	AI-based software engineering platform that accurately detects software bugs and errors, responsible for the majority of failures in major industries (specifically impacting public services), in real-time, and provides possible solutions.	Germany

2.3. ACCEPTANCE OF AI USE IN E-GOVERNMENT

Adopting AI-based technologies in e-government has far-reaching economic, legal, political, and regulatory implications (Zuiderwijk et al., 2021). However, to successfully adopt these technologies, it is paramount to explore and understand the factors leading to citizen acceptance. Previous studies have identified (i) *features of the technology itself* (usage and outcome-of-usage characteristics) and (ii) *characteristics of individual users* (demographic and psychographic characteristics) as fundamental for comprehending the attitudes, intentions, and behaviours that influence the acceptance and adoption of technology (Ittersum et al., 2006).

AI awareness, i.e. familiarity and knowledge of AI and its developments, plays a significant role in how citizens perceive AI. Citizens aware of the practical value of these technologies, due to past interactions and experiences, tend to trust them and recognize them as useful, that is, capable of improving their performance (Belanche et al., 2019; Davis, 1989; Lozano et al., 2021; Nadarzynski et al., 2019). Therefore, we propose the following hypotheses:

H1. *AI Awareness positively influences perceived usefulness of AI.*

H2. *AI Awareness positively influences trust in AI.*

One of the major concerns that arise among citizens when considering the adoption of AI, regardless of the context, is related to privacy (Fast & Horvitz, 2017; Kelley et al., 2021). In e-government, these concerns are decisive because public services deal with sensitive and confidential information, such as personal data (Cho et al., 2019). According to the Center for Strategic and International Studies (CSIS), the number of cyber incidents against government agencies has grown significantly in recent years, and citizens are increasingly concerned about how their data is collected, stored and used. Previous studies reveal that perceived usefulness and trust in AI are undermined by these concerns (Araujo et al., 2020; Cho et al., 2019). Therefore, we propose the following hypotheses:

H3. *Privacy concerns negatively influence perceived usefulness of AI.*

H4. *Privacy concerns negatively influence trust in AI.*

Previous studies reveal that online self-efficacy, i.e. belief in the self's ability to protect their privacy online, impacts perceived usefulness and trust in AI (Araujo et al., 2020). As e-government encompasses "*the use of ICTs, in particular the internet, to achieve better government*" (OECD, 2003), it is expected that citizens who believe they can protect their privacy online tend to trust AI and consider it useful because of its benefits. Therefore, we propose the following hypotheses:

H5. *Online self-efficacy positively influences perceived usefulness of AI.*

H6. *Online self-efficacy positively influences trust in AI.*

Acceptance of AI flourishes when citizens benefit from its application, i.e. when it is considered useful, in some way, for society (Lozano et al., 2021). When AI is used, citizens can benefit from rational decisions that do not account for emotions (Gesk & Leyer, 2022; Lichtenthaler, 2019). However, citizens who prefer to interact with humans due to AI's lack of empathy and technological maturity may find it hard to identify and recognize its benefits (Nadarzynski et al., 2019). We propose the following hypothesis:

H7. *Perceived usefulness of AI positively influences the acceptance of AI use in e-government.*

In the context of the adoption of technologies such as AI, trust, defined "*as a degree of trustworthy of being able to fulfil a user's purpose of usage*" (Bitkina et al., 2020), is one of the main drivers of acceptance. Therefore, we propose the following hypothesis:

H8. *Trust in AI positively influences the acceptance of AI use in e-government.*

Social influence plays an important role when citizens face disruptive change with little or no information (Taylor & Todd, 1995). In the lack of personal experience or well-formed beliefs, citizens may be influenced by interpersonal sources, e.g. opinions of peers and superiors, or external sources of information, e.g. reports and news disseminated by the media (Belanche et al., 2019; Chen & Wen, 2021). Assuming that citizens consider social influences to accept the use of AI in e-government, we propose the following hypothesis:

H9. *Social influence positively influences the acceptance of AI use e-government.*

According to Starke et al. (2020), the greater the political interest of citizens, the less their satisfaction and trust in the government. This finding reveals that citizens interested in political affairs and familiarised with the decisions made by the government have low expectations about the government's ability to produce favourable outcomes (Starke et al., 2020). In addition, previous studies reveal that citizens who trust the government tend to also trust and, consequently, accept AI use (Chen & Wen, 2021). Thus, political interest is expected to negatively impact the acceptance of AI use in e-government. We propose the following hypothesis:

H10. *Political interest negatively influences the acceptance of AI use in e-government.*

To assess the hypotheses, the following research model was outlined (Figure 1).

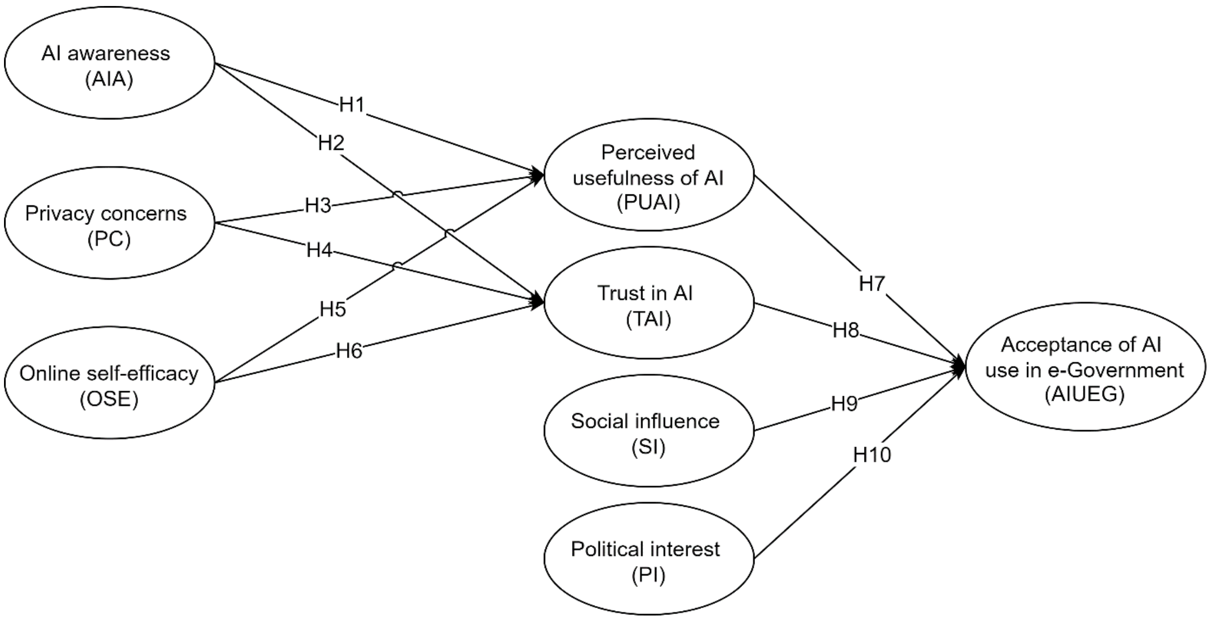


Figure 1 – Research model

3. RESEARCH METHODOLOGY

3.1. PROCEDURE

The study was conducted through an online questionnaire, developed on the Qualtrics platform, and distributed through a link sent individually through messaging apps and shared on various social networks. Before being distributed, the questionnaire was submitted, reviewed and approved by NOVA IMS Ethics Committee. It was guaranteed that the data collected was used exclusively for academic purposes, being treated in a completely anonymous and confidential manner.

3.2. MEASURES

Since the target population consists of Portuguese citizens, the questionnaire was originally designed in English and then translated to Portuguese, after that, it was back translated to English to ensure consistency (See Appendix 1).

The eight constructs of the research model were operationalized into twenty-three measurable items: *AI awareness* was measured using four items about self-reported knowledge of AI, and interest in its applications and development (adapted from Belanche et al., 2019; Gefen, 2000). *Privacy concerns* were measured with three items adapted from previous research (Baek & Morimoto, 2012). *Online self-efficacy* – people's belief in their own ability to protect their privacy and personal information online – was measured using four items (adapted from Boerman et al., 2021; LaRose & Rifon, 2007). *Perceived usefulness of AI* was measured with three items adapted from earlier research on user acceptance of information technology (Bhattacherjee, 2000; Davis, 1989). *Trust in AI* was measured using three items (adapted from Pechar et al., 2018). *Social influence* was measured using three items about interpersonal and external influence (adapted from Belanche et al., 2019; Bhattacherjee, 2000). *Political interest* was measured with two items (adapted from Marcinkowski & Starke, 2018; Starke & Lünich, 2020). The main outcome measure – *acceptance of AI use in e-government* - was measured with a single item adapted from earlier research (Nadarzynski et al., 2019): "*In the next 12 months, if available, I would use e-government powered by AI*".

To standardise the measurement scales, a seven-point Likert scale ranging from strongly disagree (1) to strongly agree (7) was used to assess each item, according to the participants' level of agreement with each statement.

An open-ended question – "*What is your opinion on the use of artificial intelligence in e-government*?" – was also included.

4. RESULTS

4.1. Sample characterization

For this study, 208 responses were collected from Portuguese citizens. 63.0% of respondents were female, predominantly aged between 18 and 24 years (54.8%). Regarding the education level, 18.3% of respondents completed up to secondary (high) school or equivalent, more than half have a bachelor's degree (55.8%), and 26.0% have a Master's degree or PhD.

The sociodemographic characterization of the sample is represented in table 4.

Table 2 – Sociodemographic characterization (N = 208)

	N	%
Age		
Between 18 and 24 years old	114	54.8
Between 25 and 31 years old	55	26.4
Between 32 and 38 years old	16	7.7
Between 39 and 45 years old	7	3.4
Between 46 and 52 years old	6	2.9
53 years or older	10	4.8
Gender		
Female	131	63.0
Male	76	36.5
Other / Prefer not to answer	1	0.5
Education Level		
Less than secondary (high) school	2	1.0
Secondary (high) school or equivalent	36	17.3
Bachelor's degree	116	55.8
Master's degree	53	25.5
PhD	1	0.5

4.2. MEASUREMENT MODEL

To assess the quality of the measurement model, we used SmartPLS, a software that uses the partial least squares path modelling method (PLS-SEM) to estimate models with the collected data. Assessing the quality of the model includes evaluating the reliability (indicator reliability and internal consistency reliability) and validity (convergent validity and discriminant validity) of the construct measures (Hair et al., 2021a).

Indicator reliability

Indicator reliability assesses the adequacy of the items (i.e., indicators) operationalized to measure the respective constructs – all standardised item loadings must be greater than 0.7 (Hair et al., 2013). Items with loadings below the defined were removed from the model to avoid distorting the results.

Internal consistency reliability

To ensure that the items operationalized to measure the same construct are consistent and mutually associated, we verified Cronbach's alpha (Cronbach, 1951) and composite reliability (Jöreskog, 1971) values. These measures consider the same thresholds: values above 0.7 are considered satisfactory and indicate high levels of reliability (Hair et al., 2013). The results in table 4 indicate that all the constructs of the study have high levels of internal consistency reliability.

Table 3 – Cronbach's Alpha and Composite Reliability

Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AIA	0.879	0.917	0.735
AIUEG	1.000	1.000	1.000
OSE	0.813	0.876	0.641
PC	0.744	0.853	0.661
PI	0.865	0.936	0.879
PUAI	0.882	0.927	0.809
SI	0.700	0.833	0.626
TAI	0.887	0.930	0.816

Note: AIA – AI awareness; AIUEG – Acceptance of AI use in e-Government; OSE – Online self-efficacy; PC – Privacy concerns; PI – Political interest; PUAI – Perceived usefulness of AI; SI – Social influence; TAI – Trust in IA.

Convergent validity

Convergent validity measures the correlation between items used to assess the same construct. The metric used to evaluate it is the average variance extracted (AVE) - the mean value of the squared loadings of the items associated with the construct. AVE must be equal to or greater than 0.5, which indicates that the items positively correlate with their respective constructs (Fornell & Larcker, 1981; Hair et al., 2013). AVE values of the constructs of this study ranged between 0.626 and 1.000, above the minimum requirement of 0.5 (Table 4).

Discriminant validity

Discriminant validity indicates the extent to which a construct is empirically distinct from other constructs in the model and can be assessed based on the Fornell–Larcker criterion or the Heterotrait-Monotrait Ratio of correlations (HTMT).

According to the criterion suggested by Fornell & Larcker (1981), the square root of a construct's AVE should be greater than the squared correlation between that same construct and all other measured constructs in the model. Yet, this approach does not reliably detect the lack of discriminant validity in common research situations (Henseler et al., 2015). Therefore, we used the HTMT since it has proven to perform better than the Fornell-Larcker criterion. The HTMT, defined as the mean correlation among items across constructs relative to the geometric-mean correlation among items measuring the same construct, must be less than 0.9 to establish discriminant validity between constructs (Henseler et al., 2015). Table 6 indicates that the criterion is fulfilled.

Table 4 – Heterotrait-Monotrait Ratio (HTMT)

	AIA	AIUEG	OSE	PC	PI	PUAI	SI	TAI
AIA								
AIUEG	0.337							
OSE	0.264	0.393						
PC	0.097	0.331	0.174					
PI	0.260	0.046	0.140	0.065				
PUAI	0.335	0.795	0.350	0.295	0.036			
SI	0.333	0.752	0.296	0.243	0.118	0.717		
TAI	0.457	0.660	0.426	0.334	0.084	0.656	0.506	

Note: AIA – AI awareness; AIUEG – Acceptance of AI use in e-Government; OSE – Online self-efficacy; PC – Privacy concerns; PI – Political interest; PUAI – Perceived usefulness of AI; SI – Social influence; TAI – Trust in IA.

4.3. STRUCTURAL MODEL

After confirming the reliability and validity of the measurement model, it is essential to assess the structural model (Hair et al., 2021b). Its assessment, made through a Bootstrapping procedure, focuses on analysing the significance of the structural model's relationships (path coefficients) and explaining the variance of its dependent variables (R^2) – perceived usefulness of AI, trust in AI and acceptance of AI use in e-government.

Collinearity

Previously, we tested the structural model for collinearity problems. When there is correlation between independent variables in the same regression model, it means that they explain part of the same variation in the dependent variable, decreasing their statistical significance (O'Brien, 2007). The collinearity of the measured items is estimated based on the Variance Inflation Factor (VIF), which must be less than 5.0 (Hair et al., 2013). Collinearity problems were not detected.

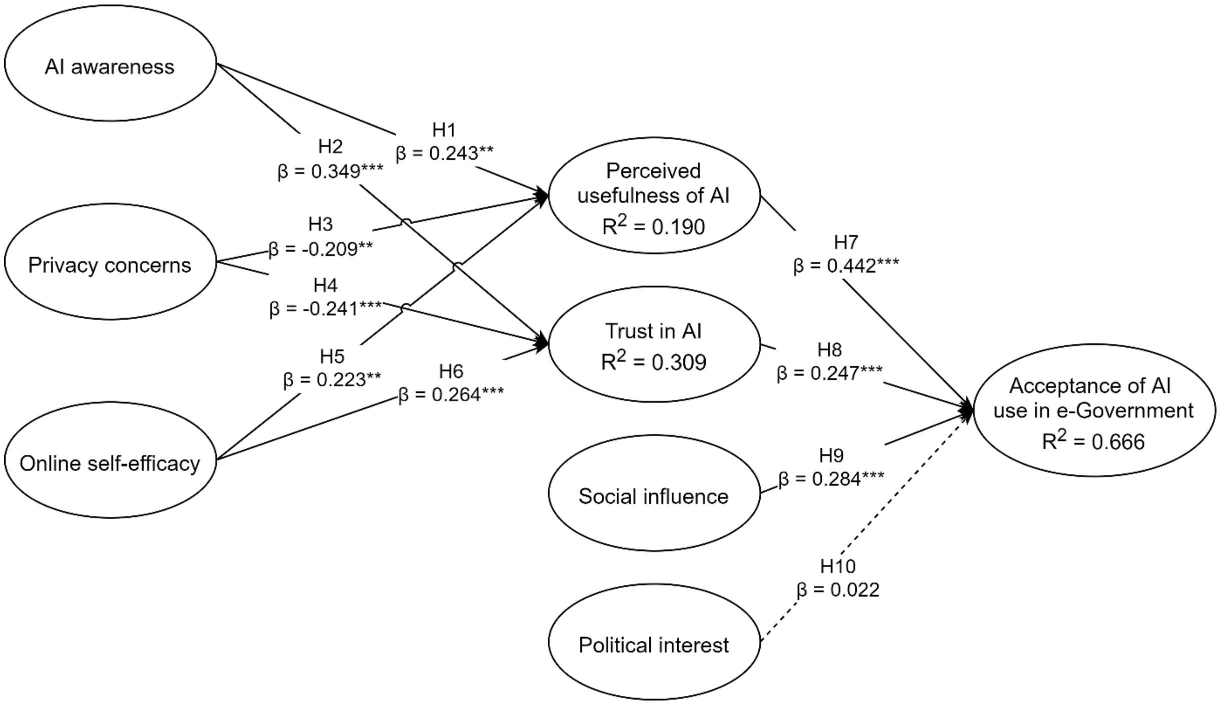
Hypothesis testing

The levels of significance dictate the rejection or acceptance of the proposed hypotheses. A result is significant if the p-value is smaller than 0.05 or greater than 0.95.

The results reveal that AI awareness ($\beta = 0.243$; $p < 0.005$) and online self-efficacy ($\beta = 0.223$; $p < 0.005$) positively influence perceived usefulness of AI. On the other hand, the perceived usefulness of AI is impacted negatively by privacy concerns ($\beta = -0.209$; $p < 0.001$). Jointly, AI awareness, privacy concerns, and online self-efficacy explain 19.0% of the variance in AI's perceived usefulness. Therefore, hypotheses 1, 3 and 5 are supported. Trust in AI is also positively impacted by AI awareness ($\beta = 0.349$; $p < 0.001$) and online self-efficacy ($\beta = 0.264$; $p < 0.001$), but negatively influenced by privacy concerns ($\beta = -0.241$; $p < 0.001$). These variables explain 30.9% of the variance in AI trust. Therefore, hypotheses 2, 4 and 6 are supported.

The results also reveal that the model explains 66.6% of the variation in acceptance of the use of AI in e-government, with the perceived usefulness of AI being the most significant predictor of the acceptance of AI use in this context ($\beta = 0.442$; $p < 0.001$). It is also explained by social influence ($\beta = 0.284$; $p < 0.001$) and by AI trust ($\beta = 0.247$; $p < 0.001$). In turn, political interest ($\beta = 0.022$; $p > 0.1$) has an insignificant effect. Therefore, the remaining hypotheses were supported, except for hypothesis 10. Of the ten hypotheses proposed, nine were supported.

The structural model and achieved results are shown in figure 2.



Note: Non-significant paths are in dashed lines. Significant at *p < 0.01; **p < 0.005; ***p < 0.001.

Figure 2 – Structural model

We also tested the indirect effects of AI awareness, privacy concerns and online self-efficacy on the acceptance of AI use in e-government. Results indicate that, statistically, these variables have meaningful effects on acceptance when mediated by AI's perceived usefulness and trust (Table 7).

Table 5 – Specific Indirect Effects

	Indirect effect	**p-Value**
AIA → PUAI → AIUEG	0.107	0.004
AIA → TAI → AIUEG	0.086	0.002
OSE → PUAI → AIUEG	0.098	0.009
OSE → TAI → AIUEG	0.065	0.005
PC → PUAI → AIUEG	-0.092	0.009
PC → TAI → AIUEG	-0.060	0.010
PC → TAI → AIUEG	-0.060	0.010

Note: AIA – AI awareness; PUAI – Perceived usefulness of AI; AIUEG – Acceptance of AI use in e-Government; TAI – Trust in AI; OSE – Online self-efficacy; PC – Privacy concerns.

4.4. MULTIGROUP ANALYSIS

To determine whether the outcomes vary based on gender, we used the PLS-MGA (multigroup analysis) approach. PLS-MGA, a non-parametric significance test, allows testing if predefined data groups have significant differences in their group-specific parameter estimates. A result is meaningful if the p-value is smaller than 0.05 or greater than 0.95 for the difference of group-specific path coefficients (Henseler et al., 2009). The results reveal significant differences between males and females concerning the impacts of AI awareness on the perceived usefulness of AI (p = 0.031) and political interest in acceptance of AI use in e-government (p = 0.031). No significant differences were found between the other path coefficients and relationships across both groups (Table 8).

Table 6 – Multigroup analysis (MGA)

	Path Coefficients-diff (Female - Male)	**p-Value original 1-tailed (Female vs Male)**	**p-Value new (Female vs Male)**
AIA → PUAI	**0.308**	**0.016**	**0.031**
AIA → TAI	0.075	0.303	0.607
OSE → PUAI	-0.205	0.944	0.112
OSE → TAI	-0.124	0.855	0.289
PC → PUAI	0.255	0.031	0.063
PC → TAI	0.103	0.197	0.394
PI → AIUEG	**0.204**	**0.016**	**0.031**
PUAI → AIUEG	0.240	0.033	0.066
SI → AIUEG	-0.168	0.945	0.111
TAI → AIUEG	-0.179	0.931	0.138

Note: AIA – AI awareness; PUAI – Perceived usefulness of AI; TAI – Trust in IA; OSE – Online self-efficacy; PC – Privacy concerns; PI – Political interest; AIUEG – Acceptance of AI use in e-Government; SI – Social influence. Significant effects in bold.

According to the bootstrapping results (See Appendix 2), AI awareness has a significant impact on females' perception of the usefulness of AI. In males, it does not have an impact statistically significant. For men, privacy concerns and online self-efficacy significantly influence the perceived usefulness of AI, unlike women, who do not seem to have their perception affected by these factors. In general, political interest does not significantly influence the acceptance of AI use in e-government. However, in the case of women, this predictor is positively significant - women interested in political affairs and familiar with the decisions taken by the government tend to accept AI use in e-government.

4.5. QUALITATIVE ANALYSIS

The measurement model also includes an open-ended question: "*What is your opinion on artificial intelligence use in e-government?*". To assess the qualitative data collected, we performed thematic content analysis and organised them into three topics: (i) *Benefits and positive attitudes*, (ii) *Fears and negative attitudes*, and (iii) *Awareness of e-government and/or AI*. Table X presents the topics and some of the most relevant responses.

Table 7 – Relevant responses concerning AI use in e-Government

Topics	Responses
Benefits and positive attitudes	*"It would be beneficial to optimise various public services."* *"It seems to be a solution that, well thought out and planned, can save us time and resources, and be very useful."* *"It can bring clear benefits to the lives of citizens, if implemented technically correctly, and if legislated comprehensively to guarantee the rights of citizens, especially their privacy, their information and their personal life."* *"It will make it much easier for people to get involved in politics."* *"It demonstrates innovation and adaptation on the part of the government."*
Fears and negative attitudes	*"Although it is already being used in certain aspects, I cannot trust the government to manage these new technologies."* *"Like any tool, its purpose depends on who uses it. In recent years we have witnessed a trans-passing of the freedoms and guarantees of citizens around the world. The stronger the tools available to governments, the greater the risk of abuse of power."* *"Current government electronic systems have some problems of integration, usability, fragmentation and resilience."* *"If at this point, we consider integrating AI into these systems, whether to automate or simplify processes, or in the digitization of the democratic process, we have to reflect on whether the current systems have the level of robustness and maturity, to the point of putting on the table, a new proposal to add even more complexity to these systems."*

Awareness of e-government and/or AI	*"I don't know what AI or e-government specifically refer to."* *"I have no idea how AI can be used in e-government."* *"It looks promising, but I don't have enough knowledge of AI to have a concrete opinion."*

Awareness of e-government and/or AI: Some participants recognized not being able to identify e-government and/or AI. Therefore they do not have a formed opinion. Participants also mentioned that they do not know how AI can be applied in e-government.

Benefits and positive attitudes: Most participants recognized the benefits of using AI in e-government, but acknowledged that its adoption must be done carefully. If regulated and implemented correctly to ensure citizens' rights, particularly security and privacy, participants believe that AI will significantly improve how governments work by optimising public processes and services, fostering civic participation and improving general well-being. In addition, it reveals innovation and adaptation on the part of the government.

Fears and negative attitudes: Many participants expressed a lack of confidence in the government to handle and control such a disruptive technology as AI. In addition to the concerns raised about the potential abuse of power, this distrust is aggravated by the unreliability of public digital platforms and, consequently, of the services delivered by them. AI use in e-government requires citizens' prior trust in these tools. However, participants highlighted that these have numerous problems and that it is necessary to determine whether current tools are prepared to host technologies as complex as AI.

5. DISCUSSION

To our knowledge, this is the first study exploring the acceptance of AI use in e-government from the perspective of the general public.

Results of the survey with a sample of the Portuguese population show that AI awareness, privacy concerns and online self-efficacy explain 19% of the variation in the perceived usefulness of AI and 31% of the variation in AI trust. AI awareness, i.e. familiarity and knowledge of AI and its developments, positively influences perceived usefulness and trust in AI. These findings, corroborated by previous studies (Araujo et al., 2020; Belanche et al., 2019; Lozano et al., 2021; Nadarzynski et al., 2019), suggest that citizens more aware of AI applications and developments tend to trust it and perceive it as useful since they have more knowledge about the practical value of these technologies and have a solid personal predisposition about the targeted behaviour - perceive AI as useful and trustworthy (Belanche et al., 2019; Castañeda et al., 2007). Privacy concerns negatively impact perceived usefulness and trust in AI, which is in line with findings from previous studies (Araujo et al., 2020). The usefulness and trust in AI are dictated by its results, i.e. its successes and failures (Hidalgo et al., 2021). If AI-based technologies fail, people are unlikely to trust and use them again. Therefore, it is essential to ensure that these technologies are able to protect the data collected and analysed. This finding is also validated by the fact that citizens who consider themselves capable of protecting their privacy online - online self-efficacy - tend to view AI as useful and trustworthy.

Results also indicate that perceived usefulness and trust in AI and social influence explain 67% of the variation in acceptance of AI use in e-government. Perceived usefulness of AI, followed by social influence, are the main drivers of acceptance of AI use in e-government, supporting previous studies (Belanche et al., 2019). Acceptance of AI thrives when citizens consider it useful for society (Lozano et al., 2021). Furthermore, both the opinions of peers and superiors (interpersonal influence) and the news disseminated by the media (external influence) impact the acceptance of the use of AI in the context of e-government. Social influence may be of particular interest to citizens facing an innovation with limited information (Taylor & Todd, 1995). In the lack of their own experience or well-formed beliefs, individuals are influenced by interpersonal and external sources of information (Belanche et al., 2019; Chen & Wen, 2021). Overall, the political interest is insignificant to the acceptance of AI use in e-government. However, in the case of women, this predictor is positively significant - women interested in political affairs and familiar with the decisions taken by the government tend to accept AI use in e-government. This finding is inconsistent with previous studies. According to Starke et al. (2020), citizens interested in politics tend to not trust the government. Since citizens who distrust the government tend to have an unfavourable perception of AI (Chen & Wen, 2021), political interest was expected to negatively influence the acceptance of AI in e-government.

Qualitative analysis shows that several participants recognize the benefits of using AI-based technologies in e-government. They believe that these technologies could significantly improve the functioning of local and national governments by optimising public processes and services, facilitating public participation and increasing well-being. However, they raise several concerns related to the lack of trust in the government to deal with and manage such a disruptive technology as AI. In addition to the concerns raised about the potential abuse of power, this distrust is aggravated by the lack of reliability of public digital platforms, mainly due to their numerous technical problems. Despite the majority of participants being aware of AI and e-government, some are not or are not aware of how AI can be used in e-government. This finding reveals that, despite AI being ubiquitous, many people who, in some way, have interacted with it didn’t even realise it.

6. CONCLUSION

As we saw earlier, the adoption of technology as powerful and disruptive as AI could be the answer to solving some of the current problems of e-government. However, for it to be successfully adopted, it is essential to understand the factors that influence its acceptance in this context. In this study, we explore the impact of relevant drivers identified in the literature (features of the technology itself and characteristics of individual users) on the acceptance of AI use in e-government.

This study indicates that the perceived usefulness of AI, followed by social influence and trust in AI, are strong predictors of acceptance of the use of AI in e-government. Though, to trust AI and recognize the benefits of using it, it is essential to be familiar with it and its applications (AI awareness). These findings suggest that governments that already use e-government and intend to incorporate AI-based technologies into it should invest in citizens' understanding that AI is already present in their daily lives and address its advantages and disadvantages. However, governments must also do it for e-government by clarifying its meaning and applications and solving its current technical problems. These investments could also result in increased trust in the government. This study can help local and national governments assess the acceptance of the adoption of AI-based technologies in e-government and define tailored strategies to respond to citizens' concerns and highlight benefits to society.

7. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORKS

Although the study brings several contributions, we recognize some limitations that may lead to opportunities for future research. The model was evaluated using a convenience sample collected in Portugal, i.e. the participants were not selected through a statistical criterion. As a consequence, caution is need when generalizing conclusions about the effects of the studied drivers on the general population. Future research may (i) take a longitudinal sample and (ii) add new constructs to facilitate subsequent comparison with other countries – for example, the inclusion of a cultural dimension in the research model (Hofstede & Hofstede, 2005).

Another limitation of the sample is related to the fact that almost two-thirds of the participants are female, and more than half are between 18 and 24 years old.

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9. APPENDIX

Appendix 1 – Measurement scales used

Constructs	Measurement items		Adapted from
AI awareness	AIA1	I'm familiar with AI	Belanche et al., 2019; Gefen, 2000
	AIA2	I'm familiar with AI-generated content (texts, images, videos, etc.)	
	AIA3	I've interacted with AI-based technologies	
	AIA5	I'm aware of AI developments	
Privacy concerns	PC1	I feel uncomfortable when I share information online	Baek & Morimoto, 2012
	PC2	I worry when I share personal data online	
	PC3	I fear the information is not secure while stored online	
Online self-efficacy	OSE1	I feel confident that I can protect my privacy online	Boerman et al., 2021; LaRose & Rifon, 2007
	OSE2	I'm able to protect my personal information (browsing history, login data, etc.) online	
	OSE3	I can easily identify sites I can trust	
	OSE4	I can ensure that companies cannot collect my personal information online	
Perceived usefulness of AI	PUAI1	The use of AI in e-government would save me time	Bhattacherjee, 2000; Davis, 1989
	PUAI3	The use of AI in e-government would facilitate my involvement in decision-making	
	PUAI4	The use of AI in e-government would be useful in my daily life	
Trust in AI	TAI1	I trust AI	Pechar et al., 2018
	TAI2	I trust the information provided by the AI	
	TAI3	I trust AI to make decisions	
Social influence	SI1	People I know think AI can improve the e-government	Belanche et al., 2019; Bhattacherjee, 2000
	SI2	People I know can influence me to try AI-powered e-government	

	SI5	Social media can influence me to try AI-powered e-government	
Political interest	PI1 PI2	I’m interested in political affairs I'm informed of the decisions taken by the political rulers	Marcinkowski & Starke, 2018
Acceptance of AI use in e-Government	AIUEG	In the next 12 months, if available, I would use e-government powered by AI	Nadarzynski et al., 2019

Appendix 2 – Bootstrapping results

	Path Coefficients Original (Female)	Path Coefficients Original (Male)	Path Coefficients Mean (Female)	Path Coefficients Mean (Male)	STDEV (Female)	STDEV (Male)	t-Value (Female)	t-Value (Male)	p-Value (Female)	p-Value (Male)
AIA -> PUAI	0.472	0.163	0.462	0.159	0.086	0.120	5.518	1.362	0.000	0.173
AIA -> TAI	0.400	0.325	0.392	0.324	0.107	0.095	3.730	3.412	0.000	0.001
OSE -> PUAI	0.150	0.355	0.159	0.366	0.084	0.096	1.796	3.719	0.073	0.000
OSE -> TAI	0.254	0.378	0.263	0.385	0.086	0.078	2.945	4.871	0.003	0.000
PC -> PUAI	-0.026	-0.281	-0.054	-0.280	0.090	0.104	0.289	2.698	0.773	0.007
PC -> TAI	-0.181	-0.283	-0.191	-0.290	0.089	0.085	2.026	3.330	0.043	0.001
PI -> AIUEG	0.128	-0.076	0.131	-0.067	0.058	0.071	2.201	1.081	0.028	0.280
PUAI -> AIUEG	0.515	0.275	0.499	0.280	0.091	0.090	5.667	3.056	0.000	0.002
SI -> AIUEG	0.197	0.365	0.208	0.365	0.064	0.081	3.081	4.496	0.002	0.000
TAI -> AIUEG	0.177	0.356	0.184	0.350	0.083	0.086	2.147	4.145	0.032	0.000