COMMUNICATION & SOCIETY

Special issue

Adoption and use factors of artificial intelligence and big data by citizens

Patricia Sánchez-Holgado
https://orcid.org/0000-0002-6253-7087
patriciasanc@usal.es
Universidad de Salamanca

Carlos Arcila-Calderón
http://orcid.org/0000-0002-2636-2849
carcila@usal.es
Universidad de Salamanca

Submitted
January 12th, 2024
Approved
February 29th, 2024

ISSN 0214-0039
E ISSN 2386-7876
www.communication-society.com

2024 – Vol. 37(2)
pp. 227-246

How to cite this article:
Sánchez-Holgado, P. & Arcila-Calderón, C. (2024). Adoption and use factors of artificial intelligence and big data by citizens, *Communication & Society, 37*(2), 227-246.
doi.org/10.15581/003.37.2.227-246

Abstract

The impact of artificial intelligence on people's lives is demonstrated today. Previous literature has shown that the use of a specific technology is directly linked to the individuals' intention to use it. The aim of this paper is to study the factors that determine the adoption and use of artificial intelligence and big data in Spain, using a research model based on the Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh *et al.* (2003). This work addresses the specific gap in the validation of the original theoretical model of UTAUT in two dimensions, with respect to the adoption of artificial intelligence by citizens and with respect to the factors that influence this adoption, evaluating the previous ones and proposing some new ones considering the current context. The methodology used is based on a national survey, and it analyzes the research model using the statistical technique of Partial Least Squares Structural Equation Modelling (PLS-SEM), which details the mediating and moderating relationships between constructs. The results show that Intention to Use has a direct positive influence on the Use of artificial Intelligence and big data, confirming previous literature. Performance Expectancy is the strongest predictor of Intention to Use, and indirectly of the adoption of artificial intelligence and big data applications. Effort Expectancy, in its application to the adoption of AI and big data by citizens, is an indirect determinant mediated by the Intention to Use, but its total effect (direct + indirect) is not significant.

Keywords
Artificial intelligence, intention to use, UTAUT, technology acceptance, PLS-SEM.

1. Introduction

Artificial intelligence (AI) is the ability of a machine to exhibit the same capabilities as humans, such as reasoning, learning, creativity, and planning capacity. AI systems can adapt their behavior to a certain extent, analyzing the effects of previous actions and working autonomously (Samoili *et al.*, 2020). On the other hand, big data refers to large amounts of data produced very quickly by various sources. Data can be created by people or generated by machines, such as sensors that collect weather information, satellite images, digital images and videos, purchase transaction records, GPS signals or others (European Commission, 2023).

Artificial intelligence is used by a multitude of applications, from healthcare or education to entertainment, which directly and significantly impacts people's lives. In healthcare, applications are being used for the diagnosis of diseases, the development of new treatments and for the automation of tasks, such as the management of medical records (Haug & Drazen, 2023; Leinweber *et al.*, 2023; Singh *et al.*, 2023). In education, artificial intelligence applications focus on personalizing learning, providing immediate feedback, and helping students in their constant training (Incio Flores *et al.*, 2021; Andreoli *et al.*, 2022; Flores-Vivar & García-Peñalvo, 2023) and big data application focus on data analysis and learning analytics, data literacy and skills training, among others (Arcila-Calderón *et al.*, 2016; Amaya-Amaya *et al.*, 2020; Bonami *et al.*, 2020; Sánchez-Holgado, 2022). In governmental and institutional issues, it is also being applied to improve the efficiency of public services, prevent fraud and in decision making with the greatest amount of structured information possible (Androniceanu, 2023; Mergel *et al.*, 2023; Salam *et al.*, 2023).

In the Spanish context, the Digital Spain agenda is the roadmap for the country's digital transformation, which acts in three key dimensions: infrastructure and technology, economy, and people. Regarding the adoption of digital technologies, from a business perspective, in 2020 Spain had a moderate rate in all sectors that exceeded the European Union average, but not that of the United States (European Investment Bank EIB, 2020). In recent years it has evolved to surpass both for platforms in the infrastructure sector and for IoT in the construction sector (EIB, 2023). In 2023, 36% of Spanish companies have adopted artificial intelligence technologies, which represents an increase of 29% from 2022 (Strand Partners, 2023).

At the same time, from a citizen perspective, 73% of consumer interactions in Spain are done digitally and 55% without the need for human assistance, compared to 58% in the rest of Europe, making digital adoption grows, but studies highlight that it requires improving the user experience (Hajro *et al.*, 2022). On the other hand, 42% of Spaniards believe that artificial intelligence and data management will generate more opportunities than risks in terms of job security and the future of work, compared to 38% who consider that it entails more risks than opportunities. and the remaining 20% who are not sure (Strand Partners, 2023). Along these lines, it has been shown that the use of technologies related to artificial intelligence and big data generates high interest among citizens, who perceive more benefits than risks in their application (Sánchez-Holgado *et al.*, 2022). In this way, both Spanish companies and citizens are very aware of the transformative potential of digital technologies.

The widespread availability of AI tools and technological applications that use big data makes us consider understanding their adoption to expand the "Unified Theory of Acceptance and Use of Technology" (UTAUT) framework because there is a gap, not only due to the novelty of these technologies, but also to the number of factors that can be considered within the framework of theories of adoption and use. The greatest application of UTAUT has been in the professional field, so the objective of this study is to apply it to the field of personal use, studying the factors that influence the adoption and use of artificial intelligence and big data on Spanish citizens in their daily lives and to what degree they affect, contributing to closing this gap.

Literature on the adoption and use of technology has strongly demonstrated that use behavior is directly linked to individuals' intention to use (Alghatrifi & Khalid, 2019; Blut *et al.*, 2021; Marikyan & Papagiannidis, 2023; Zhu *et al.*, 2017). UTAUT has the capability of explaining 70% of the intention to use a specific technology. This is much higher than the percentage achieved by previous models, which stands at 40%. Previous studies have endeavored in the application or extension of the model (Blut *et al.*, 2021; Tamilmani *et al.*, 2021), focusing on workplaces or business contexts, governance, and public services (Venkatesh, 2022; Niehaves & Plattfaut, 2010; Weerakkody *et al.*, 2014), yet we have found few studies oriented toward citizens as technology users. Venkatesh himself noted that most replications, applications, and extensions did not sufficiently include the original moderators and therefore did not examine UTAUT comprehensively (Venkatesh *et al.*, 2016). Recently, the same author points to new research that delves deeper into the adoption and use of artificial intelligence tools from the foundation of UTAUT in two main contexts, citizens, and business (Venkatesh, 2022).

From practice, it is very useful to know the mechanisms of citizen adoption, to focus on public communication strategies of artificial intelligence and data science, to identify potential risks and take measures to mitigate them, to improve training and thinking. critical of society, promoting adoption, or to design useful systems, among others.

2. Factors that influence the adoption of artificial intelligence and big data

This study adheres to a model that applies UTAUT in its original version, which was proposed by Venkatesh *et al.* (2003), to the adoption of artificial intelligence and big data (Figure 1). For this purpose, Use Behavior (UB) is defined as the degree to which an individual adopts applications that incorporate or base their functioning on AI and big data. From the Technology Acceptance Model (TAM), proposed by Davis *et al*. (1989), which predicted and evaluated the use of technology, up until UTAUT, and even going back to the Theory of Reasoned Action (TRA) formulated by Fishbein and Ajzen (1975), it has been argued that there is a direct relationship between intention to use and the adoption of a specific technology.

Behavioral Intention to use (BI) is defined as the degree to which an individual has developed conscious plans of whether to perform a specific future behavior. Previous literature confirms the positive direct effect of Intention to Use on Use Behavior (Blut *et al.*, 2021; Jadil *et al.*, 2021; Venkatesh *et al.*, 2003, 2012, 2016; Venkatesh & Davis, 2000; Williams *et al.*, 2015). Thus, we propose the following hypothesis: H1 –Intention to Use has a direct positive influence on the Use Behavior of AI and big data by citizens in their daily lives.

Performance Expectancy (PE) is defined as the degree to which the use of AI and big data will provide some benefit to the individual when performing certain activities. This construct is one of the most relevant in the UTAUT model because it is the strongest predictor of Intention to Use and Use Behavior –mediated by Intention to Use– (Compeau & Higgins, 1995; Thompson *et al.*, 1991; Venkatesh & Davis, 2000). Previous studies support this concept in diverse areas and contexts, such as online shopping (Escobar & Carvajal, 2014), business (Brünink, 2016), the use of social networks by researchers (Arcila-Calderón *et al.*, 2019), education (Mohammad-Salehi *et al.*, 2021), health (Al Aufa *et al.*, 2020), and digital banking (Jadil *et al.*, 2021), among others. The gender moderator is posited to have a stronger effect on males, based on gender differences in task orientation (Venkatesh *et al.*, 2003), while the age moderator indicates that the effect will be stronger on young people, based on the importance of the reward obtained from using a specific technology (Morris & Venkatesh, 2000). Therefore, we offer a second hypothesis: H2 –Performance Expectancy directly and positively influences the Intention to Use AI and big data by citizens, which in turn generates a positive indirect effect on Use Behavior, which is moderated by gender and age, and is stronger in males, and especially in young people.

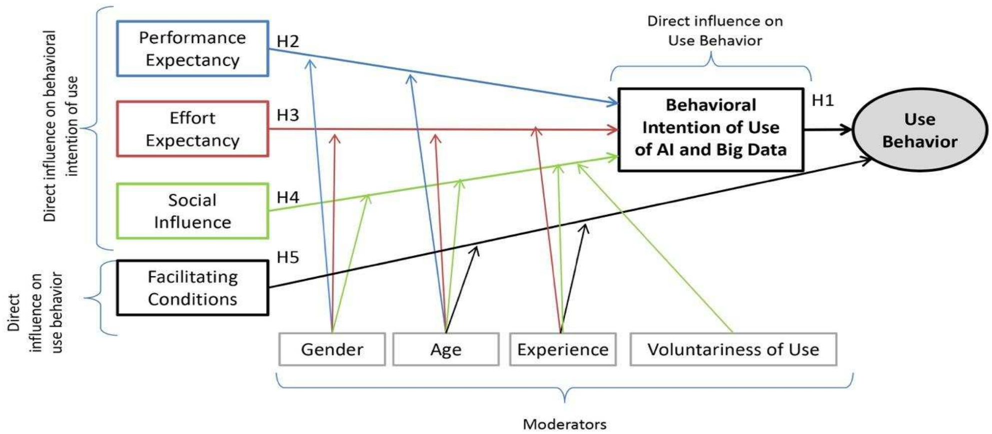
Effort Expectancy (EE) is defined as the degree of ease associated with using a specific technology and has a negative influence on the intention to use it. Previous research has shown that this construct is significant in some cases (Deng *et al.*, 2011; Martins *et al.*, 2014), but not in others (Pynoo *et al.*, 2011; Cabrera Sánchez & Villarejo Ramos, 2018a). Furthermore, gender, age and experience moderate the effect, which is stronger in women, supported by cognitive biases related to gender roles (Lynott & McCandless, 2000), yet there is no consistency, because in several studies there is no significance, or the direction is modified (Vallespín *et al.*, 2016). Therefore, we offer a third hypothesis: H3 –Effort Expectancy has a direct negative influence on the Intention to Use AI and big data by citizens, which in turn generates a negative indirect effect on its Use Behavior, which is moderated by gender, age and experience, such that it will be stronger in women, young people, and those who are less experienced.

ISSN 2386-7876 – © 2024 Communication & Society, 37(2), 227-242

Social Influence (SI) is the extent to which users perceive that the people closest to them consider the use of AI and big data appropriate. The effect is moderated by gender, age, experience, and voluntariness of use (Venkatesh *et al.*, 2003; Venkatesh & Davis, 2000). Thus, the fourth hypothesis is as follows: H4 –Social Influence (SI) has a direct positive effect on the Intention to Use AI and big data by citizens, and this generates a positive indirect influence on its Use Behavior, which is moderated by gender and age, being stronger in women and older people, and by experience and voluntariness of use, being stronger in those with less experience and those who are more compulsive.

Facilitating Conditions (FC) are defined as people's perception that they have the necessary resources and support to use AI and big data. UTAUT postulates that it only has an effect on Use Behavior, and it is moderated by age and experience, indicating that older people place more importance on having and receiving help with a specific technology, especially in work environments (Morris & Venkatesh, 2000). Based on the above, we state the fifth hypothesis: H5 –Facilitating Conditions has a direct positive effect on the Use Behavior of AI and big data by citizens, moderated by age and experience, which is stronger in older and more experienced people.

Figure 1. UTAUT research model.



Source: Own elaboration based on Venkatesh *et al*. (2003).

Based on the above, we pose the following research question (RQ1): Are the variables performance expectancy, effort expectancy, social influence, and facilitating conditions determining the intention to use and use behavior of artificial intelligence and big data by citizens?

3. Methodology

3.1. *Sample and procedure*

This study has been developed between 2020 and 2023. It is based on a national survey in which specific questions were included to study the adoption and use of artificial intelligence and big data. The constructs and indicators are shown in Annex 1. For this purpose, a questionnaire with close-ended questions was designed based on the research model of technology adoption and use theory of Venkatesh (2003), as well as the validated instrument of the UTAUT model. It was distributed online, and steps were taken to ensure that it was adequate and representative of the respondents, who were stratified by gender, age, and region, and it took place in 2020. A sample of 684 Spanish citizens was obtained, of which 54.82% were women and 44.74% were men. The age groups were distributed as follows: 8.19% were aged 18 to 24; 25% were aged 25 to 34; 30.26% were 35 to 49; 19.30% were 50 to 64; and 17.25% were over 65 years old.

3.2. *Measurements*

The socio-demographic variables included gender (0=female, 1=male, 3=DNK/DNA, others), and age (1=Under 18 years, 2=18-24 years, 3=25-34 years, 4=35-49 years, 5=50-64 years, 6=over 65 years). Use Behavior and Intention to Use was measured by utilizing several selected applications based on AI and big data, chosen as representative of people's use in their daily lives (virtual assistants, social networks, audio, and video streaming platforms). Use Behavior was measured by a dichotomous response (0. Not adopted, 1. Yes adopted). In each case, Intention to Use yielded the following reliability: virtual assistants α_c=0.93; social networks α_c=0.93; audio platforms α_c=0.94; and video platforms, α_c=0.94. Each variable used was composed of several items: Performance Expectancy (4 items, α_c=0.88); Effort Expectancy (4 items, α_c=0.90); Social Influence (3 items, α_c=0.92); Facilitating Conditions (4 items, α_c=0.87); Experience (4 items, α_c=0.85); and Voluntariness of Use (4 items, α_cc=0.90). A 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) was used for measurement, except for Performance Expectancy, which ranged from 1 (strongly agree) to 5 (strongly disagree) (Constructs and indicators are shown in Table 1). Frequency of use was measured with the same scale from never (1) to always (5). Cronbach's alpha statistic (α_c) was used to determine reliability for internal consistency, ensuring the required minimum of 0.70. All constructs and indicators are based on the original UTAUT model and can be seen in detail in Annex 1.

3.3. *Analysis*

An inductive-exploratory statistical analysis was carried out, which provided information regarding the use of artificial intelligence and big data applications that were consulted (virtual assistants, social networks, and both audio and video streaming platforms). An analysis of the proposed research model was then developed to test the hypotheses, using the statistical technique of Partial Least Squares Structural Equation Modelling (PLS-SEM) and the computer software SmartPLS version 3 (Ringle *et al.*, 2015).

4. Results

4.1. *Exploratory analysis*

The average adoption rate of AI and big data applications is 61.50%, which means that adoption is high considering the set of applications as a whole. However, the individual adoption rate varies, with social networks being the most used 89.04% (SD=0.31), followed by video streaming platforms 75.60% (SD=0.43), audio streaming platforms 60.50% (SD= 0.49), and virtual assistants 48.40% (SD=0.50). In terms of frequency of use, social networks stand out (SD=1.20), followed by video (M=3.51 SD=1.46), audio (M=3.08 SD=1.46), and virtual assistants (M=2.59 SD=1.44). Intention to Use has an overall mean of 3.91 (SD=1.08); Performance Expectancy has 3.76 (SD=1.07); Effort Expectancy stands at 2.69 (SD=1.13); Facilitating Conditions is 3.56 (SD=1.15); Experience is 3.61 (SD=1.13), and Voluntariness of Use is 3.69 (SD=1.08).

4.2. *Statistical analysis*

The reliability and consistency of the model was verified. The factor loading was determined with an exploratory factor analysis, presenting internal consistency (>0.70) (Carmines and Zeller, 1979). The internal consistency was αc>0.70 in all cases except Actual Use (αc=0.66). Convergent validity met the minimum of AVE=0.5 for each construct. (Chin, 1998; Henseler *et al.*, 2009) (Table 1).

Table 1. Reliability and validity of measurement scales.

				Convergent Validity	Composite reliability Internal consistency		
CONSTRUCT	INDICATOR	Factorial load at >0.70	t statistic	Average variance extracted. (AVE) >0.50	Cronbach's alpha (0.70-0.90)	rho_A	Composite reliability (0.70-0.90)
UB	UB - UTAUT_2_1	**.741**	33.113	.596	.661	.662	.816
	UB - UTAUT_2_3	**.784**	38.430				
	UB - UTAUT_2_4	**.791**	42.301				
BI	IUDIARIA	**.954**	194.827	.902	.945	.948	.965
	IUFRECUENTE	**.957**	167.695				
	IUFUTURA	**.938**	135.242				
PE	PE-UTAUT1	**.870**	66.332	.730	.877	.879	.915
	PE-UTAUT2	**.874**	71.592				
	PE-UTAUT3	**.847**	54.605				
	PE-UTAUT4	**.826**	44.849				
EE	EE-UTAUT1	**.864**	62.553	.770	.901	.904	.931
	EE-UTAUT2	**.892**	97.922				
	EE-UTAUT3	**.881**	70.579				
	EE-UTAUT4	**.874**	74.091				
SI	SI-UTAUT1	**.929**	116.418	.864	.921	.922	.950
	SI-UTAUT2	**.944**	170.302				
	SI-UTAUT3	**.915**	92.390				
FC	FC-UTAUT1	**.860**	62.637	.705	.861	.870	.905
	FC-UTAUT2	**.866**	72.401				
	FC-UTAUT3	**.833**	46.950				
	FC-UTAUT4	**.797**	36.680				
EXP.	EX-UTAUT1	**.762**	33.099	.678	.841	.842	.894
	EX-UTAUT2	**.851**	55.913				
	EX-UTAUT3	**.837**	42.584				
	EX-UTAUT4	**.840**	50.316				
VU	VU-UTAUT1	**.858**	63.344	.760	.895	.896	.927
	VU-UTAUT2	**.895**	88.534				
	VU-UTAUT3	**.873**	67.091				
	VU-UTAUT4	**.861**	67.937				

Source: Own elaboration.

The structural model assesses the weight and magnitude of the relationships between the different variables (Figure 2). There is no collinearity (VIF<5.0). The Pearson correlation coefficient (R^2) shows that they possess an acceptable predictive ability (BI=0.450 and UB=0.390) (Hair *et al.*, 2017). Cohen's f-distribution shows low effects as they do not exceed the value of 0.02, except for age (Age=0.101) and Intention to Use (BI=0.154) (Table 2).

ISSN 2386-7876 – © 2024 Communication & Society, 37(2), 227-242

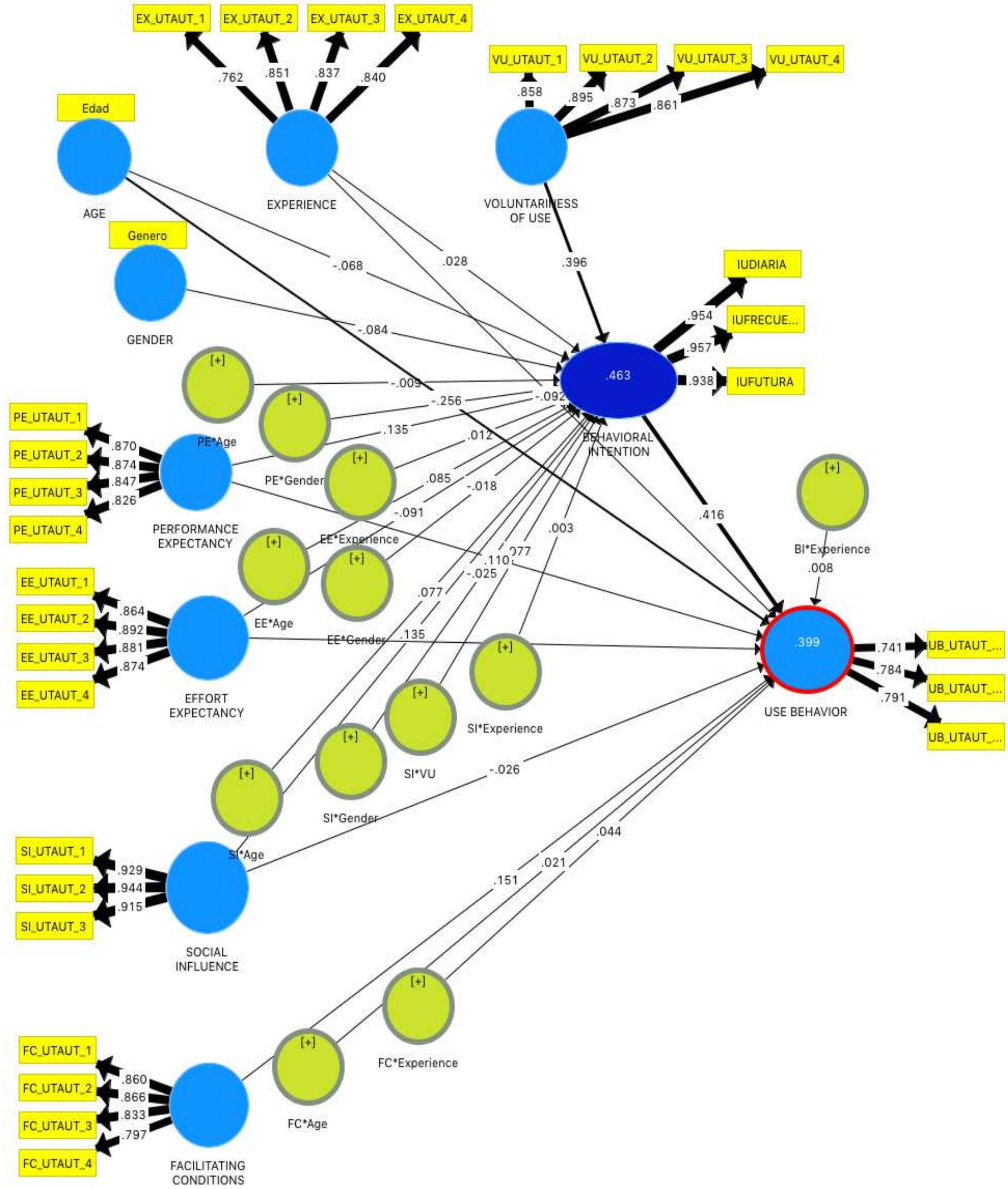
Table 2. Path coefficients (standardized regression coefficients).

	Path coefficients (Standardized two β)	Sample mean (M)	Standard deviation (STDEV)	t-value	p-value	2.5%	97.5%
BI							
PE -> BI	.135	.136	.046	2.933	.003	.045	.226
PE*Age -> BI	-.009	-.009	.041	.227	.821	-.089	.072
PE*Gender -> BI	.063	.063	.043	1.462	.144	-.023	.146
EE -> BI	-.091	-.088	.041	2.195	.028	-.171	-.008
EE*Age -> BI	.085	.084	.041	2.045	.041	.002	.166
EE*Gender -> BI	-.018	-.017	.039	.446	.656	-.095	.060
EE*Experience -> BI	.012	.014	.040	.309	.757	-.066	.093
SI -> BI	.135	.133	.043	3.129	.002	.048	.217
SI*Age -> BI	.077	.079	.045	1.686	.092	-.008	.170
SI*Gender -> BI	-.025	-.024	.047	.525	.600	-.118	.068
SI*Experience -> BI	.003	.004	.041	.078	.938	-.074	.085
SI*VU -> BI	.077	.077	.037	2.083	.037	.005	.151
AGE -> BI	-.068	-.069	.031	2.213	.027	-.130	-.010
GENDER -> BI	-.084	-.084	.031	2.709	.007	-.144	-.022
EXPERIENCE -> BI	.028	.029	.048	.581	.561	-.064	.123
VU -> BI	.396	.398	.053	7.500	.000	.294	.502
	Path coefficients (Standardized two β)	Sample mean (M)	Standard deviation (STDEV)	t-value	p-value	2.5%	97.5%
UB							
BI -> UB	.416	.415	.040	10.362	.000	.333	.491
BI*Experience -> UB	.008	.010	.034	.251	.802	-.053	.080
PE -> UB	.110	.112	.041	2.704	.007	.032	.193
EE -> UB	-.042	-.041	.043	.966	.334	-.127	.042
SI -> UB	-.026	-.027	.039	.657	.511	-.103	.050
FC -> UB	.151	.154	.048	3.134	.002	.062	.250
FC*Age -> UB	.021	.022	.028	.747	.455	-.032	.078
FC*Experience -> UB	.044	.042	.027	1.647	.100	-.011	.094
AGE -> UB	-.256	-.256	.031	8.318	.000	-.316	-.195
EXPERIENCE -> UB	-.092	-.093	.042	2.183	.029	-.177	-.011

Source: Own elaboration.

ISSN 2386-7876 – © 2024 Communication & Society, 37(2), 227-242

Figure 2. Results of the proposed model: loading values and path model.



Note: latent variables are included with the loadings of their constructs and the coefficients of each established path are shown (see detail in Table 2).

Source: Own elaboration.

4.3. *Analysis of mediation and moderation effects*

In the results of the structural model, the basic structure of UTAUT is confirmed (Table 3). In the case of Use Behavior (the adoption of applications of AI and big data), looking only at the direct effects they are significant in PE and FC (R^2=0.399). Regarding to Intention to Use (BI), looking only at the direct effects, they are significant in PE, EE and SI. BI exerts a positive direct effect on UB which is significant (B=0.416, p=.000, CI=.333 to 0.491). In the hypothesis test, this result supports H1: BI has a direct positive influence on the Use of artificial Intelligence and big data by citizens in their daily life BI–>UB (B=0.416; t=10.362; p<.001) (R^2=0.463).

It can be observed that the independent variable Performance Expectancy (PE) exerts a positive direct effect on UB that is significant (B=0.110, p=.007, CI=.32 to 0.193). The direct effect of PE on BI is also significant (B=0.135, p=.003, CI=.45 to 0.226), as well as the positive indirect effect of PE on UB, mediated through BI (B=0.056, p=.006, CI=.18 to 0.098). The total effect, considering direct effect and interaction, is significant (B=0.166, p=.000, CI=.81 to 0.254). However, in the moderators, neither gender (B=0.026, p=.146, CI= -0.009 to 0.061) nor age (B=-0.004, p=.821, CI= -0.037 to 0.029) was significant. This result partially confirms H2, as Performance Expectancy (PE) has a positive influence on the Intention to Use artificial Intelligence and big data by citizens in their daily life, which in turn generates a positive and significant indirect effect on Use Behavior PE->BI->UB (B=0. 056; t=2.770; p<.01), yet the effect is not moderated by gender (B=0.026; t=1.453; p=.146), nor age (B=-0.004; t=.226; p=.821).

About Effort Expectancy (EE), it has been observed that it exerts a negative direct effect on UB, which is not significant (B=-0.042, p=.334, CI= -0.127 to 0.042). However, the direct effect of EE on BI is significant (B=- 0.091, p=.028, CI= -0.171 to -0.008). The indirect effect of EE on UB, through BI, is significant (B= -0.038, p=.032, CI= -0.072 to -0.003), but the total effect is not (B=-0.079, p=.077, CI= -0.167 to 0.007). In the case of moderators, gender is not significant (B=-0.007, p=.657, ICC=from -0.040 to 0.024), nor is experience (B=0.005, p=.757, from -0.028 to 0.039), yet age is significant (B=0.035, p=.041, from 0.001 to 0.069). This result partially confirms H3, as Effort Expectancy (EE) has a significant negative direct effect on Intention to Use artificial intelligence and big data by citizens in their daily life, which in turn generates a negative indirect effect on Use Behavior, which is significant EE->BI->UB (B=-0. 038; t=2.150; p<.05) but is not moderated by gender (B=-0.007; t=.444; p=.657), nor experience (B=0.005; t=.309; p=.757), but the interaction of age (B=0.035; t=2.047; p<.05) is significant.

The independent variable Social Influence (SI) exerts a negative direct effect on UB, which is not significant (B=-0.026, p=.511, CI= -0.103 to 0.050). However, the direct effect of SI on BI is positive and significant (B=0.135, p=.002, CI= 0.048 to 0.217). The indirect effect of SI on UB, through BI, was also positive and significant (B=0.056, p=.003, CI=.019 to 0.093). The total effect was not significant (B=0.030, p=.486, CI= -0.057 to 0.116), and as for the moderators, gender was not significant (B=-0.010, p=.601, CI= -0. 050 to 0.028), nor age (B=0.32, p=.100, CI= -0.004 to 0.073), nor experience (B=0.001, p=.938, CI= -0.032 to 0.036), but voluntariness of use was significant (B=0.032, p=.039, CI= 0.002 to 0.063). This result partially confirms H4, as Social Influence (SI) has a positive direct effect on the Intention to Use artificial intelligence and big data by citizens in their daily life, which in turn generates a significant positive indirect effect on its use SI->BI->UB (B=0.056; t=2.967; p<. 01), yet the total effect is not significant SI->UB (B=0.030; t=.696; p=.486), nor is it moderated by gender (B=-0.010; t=.523; p=. 601), nor age (B=0.032; t=1.647; p=.100), nor experience (B=0.001; t=0.078; p=.938), yet it is moderated by voluntariness of use (B=0.032; t=2.068; p<.05).

Finally, Facilitating Conditions (FC) exert a positive direct effect on UB that is significant (B=0.151, p=.002, CI=.062 to 0.250), but is not moderated by age (B=0.021, p=.455, CI=-from 0.032 to 0.078), nor experience (B=0.044, p=.100, CI= from-0.032 to 0.078). This result partially confirms H5, as Facilitating Conditions (FC) have a significant direct effect on the use of artificial intelligence and big data by citizens in their daily life FC->UB (B=0.151; t=3.134; p>.01), but the effect of the age moderator was not significant (B=0.021; t=.747; p=.455), nor experience (B=0.044; t=1.647; p=.100).

ISSN 2386-7876 – © 2024 Communication & Society, 37(2), 227-242

Table 3. Results of the structural modelling.

	DIRECT	INDIRECT TOTAL	TOTAL EFFECT
Behavioural Intention (BI)			
R^2 / Adj. R^2	.463 / .450		
Performance Expectancy (PE)	.135**		.135**
PE*Age -> BI	-.009		-.009
PE*Gender -> BI	.063		.063
Effort Expectancy (EE)	-.091*		-.091**
EE*Age -> BI	.085*		.085*
EE*Gender -> BI	-.018		-.018
EE*Experience -> BI	.012		.012
Social Influence (SI)	.135**		.135**
SI*Age -> BI	.077		.077
SI*Gender -> BI	-.025		.003
SI*Experience -> BI	.003		-.025
SI*VU -> BI	.077*		.077*
Age	-.068*		-.068*
Gender	-.084**		-.084**
Experience	.028		.028
Voluntariness of Use (VU)	.396***		.396***
	DIRECT	INDIRECT TOTAL	TOTAL EFFECT
Use Behaviour (UB)			
R^2 / Adj. R^2	.399 / .390		
Behavioural Intention (BI)	.416***		.416***
BI*Experience -> UB	.008		.008
Performance Expectancy (PE)	.110**	.056**	.166***
PE*Age -> UB		-.004	-.004
PE*Gender -> UB		.026	.026
Effort Expectancy (EE)	-.042	-.038*	-.079
EE*Age -> UB		.035*	.035*
EE*Gender -> UB		-.007	-.007
EE*Experience -> UB		.005	.005
Social Influence (SI)	-.026	.056**	.030
SI*Age -> UB		.032	.032
SI*Gender -> UB		-.010	-.010
SI*Experience -> UB		.001	.001
SI*VU -> UB		.032*	.032*
Facilitating Conditions (FC)	.151**		.151**
FC*Age -> UB	.021		.021
FC*Experience -> UB	.044		.044
Age	-.256***	-.028*	-.284***
Gender		-.035*	-.035**
Experience	-.092*	.011	-.081
Voluntariness of Use (VU)		.165***	.165***

Note: *p<0.05; **p<0.01; ***p<0.001.

Source: Own elaboration.

5. Conclusions and discussion

The research model based on UTAUT has been relevant to study the factors that influence the adoption and use of AI and big data in citizens, through applications in their daily lives, so that we have expanded knowledge about this issue with the study of classic factors and the need to study new factors specific to artificial intelligence and the use of data arises.

Intention to Use is the main direct predictor of the adoption of a specific technology, confirming previous literature. Indirectly, Use Behavior is determined by the user's perception of the performance of the technology and the benefits it provides; the degree of perceived ease; the degree to which people close to them consider the use of the technology appropriate; and the resources necessary for its use.

The Intention to Use AI and big data applications is directly determined by the user's perception of the performance of the technology and the benefits it will bring; the ease of use; and the degree to which people close to them consider it appropriate to use the technology.

Effort Expectancy, in its application to the adoption of AI and big data by citizens, is an indirect determinant mediated by the Intention to Use, but its total effect (direct + indirect) is not significant. This may be because the technology itself is complex and is assumed to have certain difficulties of use, yet it does not influence people's intention, which has also been seen in previous studies (Cabrera-Sánchez & Villarejo Ramos, 2018b).

The Facilitating Conditions are also more linked to the professional field, since the tools of application in people's daily lives are of their own choosing, which is a factor that loses strength in this new framework of application.

In the moderating role of the Voluntariness of Use, it can also be considered that its effects are influenced by the obligatory nature linked to the professional realm, given that establishing this situation in private use is difficult. All technologies have a learning curve that can influence their early adoption, but in the case of AI and big data applied to everyday use, we know that they generate a lot of interest, and that the valuation of their benefits is higher than that of their risks (Sánchez-Holgado *et al.*, 2022). This makes us reflect on the need for people to understand the possibilities offered by these technologies, their applications, benefits, and risks, so that they have the critical capacity to decide to adopt them according to their needs.

New lines of research are therefore opened to extend the theoretical model of UTAUT to the adoption of AI by citizens. The use of AI tools and applications entails "an increase in gender and ethnic prejudices, significant threats to privacy, dignity and agency, the dangers of mass surveillance and the increase of use of unreliable artificial intelligence technologies in law enforcement" (UNESCO, 2021). Based on this, one of the determining moderating factors to add to the model is the perception of data privacy by users (Fernández-Aller & Serrano Pérez, 2022), as it can affect the use that individuals make of AI applications, which is especially appreciated in health issues (Dhagarra *et al.*, 2020; Abdullah & Fakieh, 2020; Gerke *et al.*, 2020; Lee & Yoon, 2021; Sebastian *et al.*, 2023), finance (Mhlanga, 2020; Mandala *et al.*, 2022; Hentzen *et al.*, 2022), and governance (Saura *et al.*, 2022; Medaglia *et al.*, 2023). Privacy perception is understood as the perception of risk regarding the privacy of the personal data available to the application. This variable requires an analysis of the moderation it can exert on the intention to use.

Another factor that can influence the intention to use AI is individuals' knowledge of the biases present in the algorithms. Intention to use and can be moderated by a person's knowledge of existing biases, applied at each step of the process, such as data collection, annotation, development of machine learning models, evaluation, implementation, operationalization, monitoring, and feedback integration (Chen *et al.*, 2023).

Finally, the mediating role of the Trust factor should be studied (Langer *et al.*, 2022; Benda *et al.*, 2022; Ingrams *et al.*, 2021; Tucci *et al.*, 2022; Solberg *et al.*, 2022), and once its importance in individual decision-making has been demonstrated, it is appropriate to include it as a determinant of the use of a technology.

Some limitations of the work focus on the understanding of the concepts related to the use of applications and tools of AI and big data. The individual' perception is being measured, but not their actual knowledge about this type of technology, so a realistic bias may be that their training on the subject is not sufficient to understand its performance.

Future lines of work, therefore, orient towards the study of new factors that may have greater relevance for adoption, considering the concerns that citizens show about data privacy, ethics or algorithmic biases and the attitudes they show. towards risks. In this way,

ISSN 2386-7876 – © 2024 Communication & Society, 37(2), 227-242

social perception studies can be combined with those of adoption and use, to clearly identify the factors with the greatest influence and work on them, which requires further interdisciplinary research.

This study is part of the research projects "Data Science in Spain: knowledge and public perception of big data and artificial intelligence" and "The social perception of Artificial Intelligence in Spain," funded by the Spanish Foundation for Science and Technology (FECYT) within the Call for aid to promote scientific, technological and innovation culture (FCT-18-13437 and FCT-21-17146).

References

Abdullah, R. & Fakieh, B. (2020). Health care employees' perceptions of the use of artificial intelligence applications: Survey study. *Journal of Medical Internet Research*, *22*(5), 1–8. https://www.doi.org/10.2196/17620

Al Aufa, B., Renindra, I. S., Putri, J. S. & Nurmansyah, M. I. (2020). An application of the Unified Theory of Acceptance and Use of Technology (UTAUT) model for understanding patient perceptions on using hospital mobile application. *Enfermería Clínica*, *30*, 110-113. https://www.doi.org/10.1016/j.enfcli.2020.06.025

Alghatrifi, I. & Khalid, H. (2019). A Systematic Review of UTAUT and UTAUT2 as a Baseline Framework of Information System Research in Adopting New Technology: A case study of IPV6 Adoption. *6th International Conference on Research and Innovation in Information Systems* (ICRIIS) (pp. 1-6), Johor Bahru, Malaysia. https://www.doi.org/10.1109/ICRIIS48246.2019.9073292

Amaya-Amaya, A., Huerta-Castro, F. & Flores-Rodríguez, C. O. (2020). Big Data, a strategy to avoid school dropouts in HEIs. *Revista Iberoamericana de Educación Superior*, *11*(31), 166-178. https://www.doi.org/10.22201/iisue.20072872e.2020.31.712

Andreoli, S., Batista, A., Fucksman, B., Gladko, L. & Martínez, K. (2022). *Artificial intelligence and education A framework for the analysis and creation of experiences at the higher level*. Buenos Aires: Universidad de Buenos Aires (CITEP). Retrieved from http://citep.rec.uba.ar/publicaciones

Androniceanu, A. (2023). The new trends of digital transformation and artificial intelligence in public administration. *Administratie si Management Public*, *40*, 147-155. https://www.doi.org/10.24818/amp/2023.40-09

Arcila-Calderón, C., Barbosa-Caro, E. & Cabezuelo-Lorenzo, F. (2016). Big data techniques: large-scale text analysis for scientific and journalistic research. *El Profesional de la información*, *25*(4), 623-631. https://www.doi.org/10.3145/epi.2016.jul.12

Arcila-Calderón, C., Calderín-Cruz, M. & Sánchez-Holgado, P. (2019). Adoption of social networks by scientific social science journals. *El Profesional de la Información*, 28(1), 1699-2407. https://www.doi.org/10.3145/epi.2019.ene.05

Benda, N. C., Novak, L. L., Reale, C. & Ancker, J. S. (2022). Trust in AI: why we should be designing for APPROPRIATE reliance. *Journal of the American Medical Informatics Association*, *29*(1), 207-212. https://www.doi.org/10.1093/jamia/ocab238

Blut, M., Yee, A., Chong, L., Tsiga, Z., Venkatesh, V. & Tech, V. (2021). Meta-Analysis of the Unified Theory of acceptance and use of technology (UTAUT): challenging its validity and charting a research agenda in the red ocean. *Journal of the Association for Information Systems*, *23*(1), 13-95. https://www.doi.org/10.17705/1jais.00719

Bonami, B., Piazentini, L. & Dala-Possa, A. (2020). Education, Big Data and Artificial Intelligence: Mixed methods in digital platforms. *Comunicar, 65*, 43-52. https://www.doi.org/10.3916/C65-2020-04

Brünink, L. (2016). *Cross-Functional Big Data Integration: Applying the Utaut Model*. Master dissertation, University of Twente. Retrieved from https://bit.ly/3maqSoK

Cabrera-Sánchez, J.-P. & Villarejo Ramos, Á. F. (2018a). Factors that affect the adoption of Big Data as a marketing instrument in Spanish companies. *Interioridade e Competitividade: Desafios Globais Da Gestâo. XXVIII Jornadas Luso-Espanholas de Gestâo Científica (2018)*, (pp. 1-13). Retrieved from https://bit.ly/3NRn2Wi

Cabrera-Sánchez, J.-P. & Villarejo Ramos, Á. F. (2018b). Extending the UTAUT model to evaluate the factors that affect the adoption of Big Data in Spanish companies. *Nuevos Horizontes del marketing y de la distribución comercial*, *March 2020* (pp. 181-200). Retrieved from https://bit.ly/3x5VVA3

Carmines, E. & Zeller, R. (1979). *Reliability and validity assessment*. Beverly, CA: Sage.

Chen, You, W. Clayton, E., Lovett Novak, L., Anders, S. & Malin, B. (2023). Human-Centered Design to Address Biases in Artificial Intelligence. *Journal of Medical Internet Research*, *25*(1), e43251. https://www.doi.org/10.2196/43251

Chin, W. W. (1998). The partial least squares approach for structural equation modeling. In *Modern methods for business research* (pp. 295-336). Mahwah, NJ: Lawrence Erlbaum.

Chin, W. W., Marcelin, B. L. & Newsted, P. R. (2003). A partial least squares latent variable modelling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research*, *14*(2). https://www.doi.org/10.1287/isre.14.2.189.16018

Compeau, D. R. & Higgins, C. A. (1995). Application of social cognitive theory to training for computer skills. *Information Systems Research*, *6*(2), 118-143. https://www.doi.org/10.1287/isre.6.2.118

Deng, S., Liu, Y. & Qi, Y. (2011). An empirical study on determinants of web-based question-answer services adoption. *Online Information Review*, *35*(5), 788-798. https://www.doi.org/10.1108/14684521111176507

Dhagarra, D., Goswami, M. & Kumar, G. (2020). Impact of Trust and Privacy Concerns on Technology Acceptance in Healthcare: An Indian Perspective. *International Journal of Medical Informatics*, *141*, 104164. https://www.doi.org/10.1016/J.IJMEDINF.2020.104164

Escobar-Rodríguez, T. and Carvajal-Trujillo, E. (2014). Online purchasing tickets for low-cost carriers: An application of the unified theory of acceptance and use of technology (UTAUT) model. *Tourism Management*, *43*, 70-88. https://www.doi.org/10.1016/j.tourman.2014.01.017

European Commission (2023) *Digital future of Europe*. Retrieved from https://digital-strategy.ec.europa.eu/es/policies/big-data

European Investment Bank (EIB) (2020). *Who is prepared for the new digital age? Evidences from the EIB Survey*. EIB Economics Department. https://www.doi.org/10.2867/03951

European Investment Bank (EIB), (2023). *Digitalisation in Europe 2022-2023. Evidence from the EIB Investment Survey*. https://www.doi.org/10.2867/745542

Fernández-Aller, C. & Serrano Pérez, M. M. (2022). Is Data Protection-friendly Artificial Intelligence Possible? *Doxa. Cuadernos de Filosofía del Derecho*, *45*, 307-336. https://www.doi.org/10.14198/DOXA2022.45.11

Flores-Vivar, J. M. & García-Peñalvo, F. J. (2023). Reflections on the ethics, potential, and challenges of artificial intelligence in the framework of quality education (SDG4). *Comunicar*, *30*(74), 35-44. https://www.doi.org/10.3916/C74-2023-03

Gerke, S., Minssen, T. & Cohen, G. (2020). Ethical and legal challenges of artificial intelligence-driven healthcare. *Artificial Intelligence in Healthcare*, 295-336. https://www.doi.org/10.1016/B978-0-12-818438-7.00012-5

Hair, J. F., Hult, G. T., Ringle, C. M. & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Thousand Oaks, CA: Sage.

Hajro, N., Hjartar, K., Jenkins, P. & Vieira, B. (2022). *Digital Sentiment Survey in Europe*. McKinsey. Retrieved from https://bit.ly/4bPqQ79

Haug, C. J. & Drazen, J. M. (2023). Artificial Intelligence and Machine Learning in Clinical Medicine, 2023. *New England Journal of Medicine*, *388*(13), 1201-1208. https://www.doi.org/10.1056/NEJMra2302038

Hee Lee, D. & Yoon, S. N. (2021). Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges. *International Journal of Environmental Research and Public Health*, *18*(1), 1-18. https://www.doi.org/10.3390/ijerph18010271

Henseler, J., Ringle, C. M. & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, *20*(Jan.), 277-319. https://www.doi.org/10.1108/S1474-7979(2009)0000020014

Henseler, J., Ringle, C. M. & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135. https://www.doi.org/10.1007/s11747-014-0403-8

Hentzen, J. K., Hoffmann, A., Dolan, R. and Pala, E. (2022). Artificial intelligence in customer-facing financial services: a systematic literature review and agenda for future research. *International Journal of Bank Marketing*, *40*(6), 1299-1336. https://www.doi.org/10.1108/IJBM-09-2021-0417

Incio Flores, F. A., Capuñay Sanchez, D. L., Estela Urbina, R. O., Valles Coral, M. Á., Vergara Medrano, E. E. and Elera Gonzales, D. G. (2021). Artificial intelligence in education: a review of the literature in international scientific journals. *Apuntes Universitarios*, *12*(1), 353-372. https://www.doi.org/10.17162/au.v12i1.974

Ingrams, A., Kaufmann, W. & Jacobs, D. (2022). In AI we trust? Citizen perceptions of AI in government decision making. *Policy and Internet*, *14*(2), 390-409. https://www.doi.org/10.1002/poi3.276

Jadil, Y., Rana, N. P. & Dwivedi, Y. K. (2021). A meta-analysis of the UTAUT model in the mobile banking literature: The moderating role of sample size and culture. *Journal of Business Research*, *132*, 354-372. https://www.doi.org/10.1016/j.jbusres.2021.04.052

Jain, R., Garg, N. & Khera, S. N. (2022). Adoption of AI-Enabled Tools in Social Development Organizations in India: An Extension of UTAUT Model. *Frontiers in Psychology*, *13*(June). https://www.doi.org/10.3389/fpsyg.2022.893691

Langer, M., König, C. J., Back, C. & Hemsing, V. (2022). Trust in Artificial Intelligence: Comparing Trust Processes Between Human and Automated Trustees in Light of Unfair Bias. *Journal of Business and Psychology*, 0123456789. https://www.doi.org/10.1007/s10869-022-09829-9

Leinweber, J., Alber, B., Barthel, M., Whillier, A. S., Wittmar, S., Borgetto, B. and Starke, A. (2023). Technology use in speech and language therapy: digital participation succeeds through acceptance and use of technology. *Frontiers in Communication*, 8. https://www.doi.org/https://www.doi.org/10.3389/fcomm.2023.1176827

Lynott, P. P. and McCandless, N. J. (2000). The Impact of Age vs. Life Experiences on the Gender Role Attitudes of Women in Different Cohorts. *Journal of Women and Aging*, *12*(2), 5-21. https://www.doi.org/10.1300/j074v12n01_02

Mandala, G. Naidu, B., Dharam, A., Mahalakshmi, H. S., Othman, B. & Almashaqbeh, H. A. (2022). A Critical Review of Applications of Artificial Intelligence (AI) and its Powered Technologies in the Financial Industry. *2nd International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2022*, (pp. 2362-2365). https://www.doi.org/10.1109/ICACITE53722.2022.9823776

Martins, C., Oliveira, T. & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management*, *34*, 1-13. https://www.doi.org/10.1016/j.ijinfomgt.2013.06.002

Marikyan, D. & Papagiannidis, S. (2023). Unified Theory of Acceptance and Use of Technology: A review. In S. Papagiannidis (Ed.), *TheoryHub Book*. https://www.doi.org/10.4018/ijskd.2020070105

Medaglia, R., Gil-García, J. R. & Pardo, T. A. Artificial Intelligence in Government: Taking Stock and Moving Forward. *Social Science Computer Review*, *41*(1), 123-140. https://www.doi.org/10.1177/08944393211034087

Mergel, I., Dickinson, H., Stenvall, J. & Gasco, M. (2023). Implementing AI in the public sector. *Public Management Review*, *0*(0), 1-13. https://www.doi.org/10.1080/14719037.2023.2231950

Mhlanga, D. (2020). Industry 4.0 in finance: the impact of artificial intelligence (AI) on digital financial inclusion. *International Journal of Financial Studies*, *8*(3), 1-14. https://www.doi.org/10.3390/ijfs8030045

Mohammad-salehi, B., Vaez-Dalili, M. & Heidari Tabrizi, H. (2021). Investigating Factors that Influence EFL Teachers' Adoption of Web 2.0 Technologies: Evidence from Applying the UTAUT and TPACK. *The Electronic Journal for English as a Second Language,* 25(1), 1-21. Retrieved from https://bit.ly/3tdvuHA

Morris, M. G. & Venkatesh, V. (2000). Age Differences in Technology Adoption Decisions: Implications for a Changing Workforce. *Personnel Psychology*, *53*(2), 375-403. https://www.doi.org/10.1111/j.1744-6570.2000.tb00206.x

Niehaves, B. & Plattfaut, R. (2010). The age-divide in private Internet usage: A quantitative study of technology acceptance. *16th Americas Conference on Information Systems*, 1-14. Retrieved from https://bit.ly/3PToOFb

Pynoo, B., Devolder, P., Tondeur, J., van Braak, J., Duyck, W. & Duyck, P. (2011). Predicting secondary school teachers' acceptance and use of a digital learning environment: A cross-sectional study. *Computers in Human Behaviour*, *27*, 568-575. https://www.doi.org/10.1016/j.chb.2010.10.005

Ringle, C. M., Wende, S. and Becker, J. M. (2015). *SmartPLS 3*. Boenningstedt: SmartPLS GmbH. Retrieved from https://bit.ly/3teYGOi

Salam, R., Sinurat, M., Izzatussolekha, Y., Akhmad and Sacipto, R. (2023). Implementation of Artificial Intelligence in Governance: Potentials and Challenges. *Influence: international journal of science review*, *5*(1), 243-255. Retrieved from https://influence-journal.com/index.php/influence/article/view/122

Samoili, S., López Cobo, M., Gómez, E., De Prato, G., Martínez-Plumed, F. & Delipetrev, B. (2020). AI Watch - Defining Artificial Intelligence. Towards an operational definition and taxonomy of artificial intelligence. In *Joint Research Centre (European Commission)*. https://www.doi.org/10.2760/382730

Sánchez-Holgado, P. (2022). Data Science as a transversal competence in Secondary Education in Spain. In S. Carrascal Domínguez & N. Camuñas Sánchez-Paulete (Eds.), *Docencia y Aprendizaje. Competencias, identidad y formación del profesorado* (pp. 419-450). Valencia: Tirant lo Blanc.

Sánchez-Holgado, P., Arcila-Calderón, C. & Blanco-Herrero, D. (2022). Knowledge and attitudes of Spanish citizens about big data and artificial intelligence. *Revista ICONO 14. Revista Científica De Comunicación y Tecnologías Emergentes*, 20(1). https://www.doi.org/10.7195/ri14.v21i1.1908

Saura, J. R., Ribeiro-Soriano, D. & Palacios-Marqués, D. (2022). Assessing behavioral data science privacy issues in government artificial intelligence deployment. *Government Information Quarterly*, *39*(4). https://www.doi.org/10.1016/j.giq.2022.101679

Sebastian, G., George, A. & Jackson Jr., G. (2023). Persuading Patients Using Rhetoric to Improve Artificial Intelligence Adoption: Experimental Study. *Journal of Medical Internet Research*, *25*(1), e41430. https://www.doi.org/10.2196/41430

Singh, L. K., Khanna, M. & Singh, R. (2023). Artificial intelligence based medical decision support system for early and accurate breast cancer prediction. *Advances in Engineering Software*, *175*(Oct. 2022), 103338. https://www.doi.org/10.1016/j.advengsoft.2022.103338

Solberg, E., Kaarstad, M., Eitrheim, M. H. R., Bisio, R., Reegård, K. & Bloch, M. (2022). A Conceptual Model of Trust, Perceived Risk, and Reliance on AI Decision Aids. In *Group and Organization Management,* 47(2). https://www.doi.org/10.1177/10596011221081238

Strand Partners (2023). *Unlocking the potential of AI in Europe in the Digital Decade*. Ed. Amazon Web Services (AWS). Retrieved from https://assets.aboutamazon.com/c0/03/ef4cf5f941ed9dbd3e68f075ac18/unlockingeuropesaipotential-spa-report-es.pdf

Tamilmani, K., Rana, N. P., Fosso Wamba, S. & Dwivedi, R. (2021). The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): A systematic literature review and theory evaluation. *International Journal of Information Management*, *57*(Apr. 2020), 102269. https://www.doi.org/10.1016/j.ijinfomgt.2020.102269

Thompson, R. L., Higgins, C. A. & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly: Management Information Systems*, *15*(1), 125-142. https://www.doi.org/10.2307/249443

Tucci, V., Saary, J. & Doyle, T. E. (2022). Factors influencing trust in medical artificial intelligence for healthcare professionals: a narrative review. *Journal of Medical Artificial Intelligence*, *5*(Aug. 2021), 0-2. https://www.doi.org/10.21037/jmai-21-25

Vallespín, M., Molinillo, S. & Pérez-Aranda, J. (2016). The influence of age and gender on the determinants of mobile channel adoption for travel planning. In P. Correia, M. Santos, J. A. C. Santos & M. Aguas (Edd.), *Tourism & Management Studies International Conference TMS* (p. 176). Retrieved from https://bit.ly/3ma8rJN

Venkatesh, V. & Davis, F. D. (2000). Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, *46*(2), 186-204. https://www.doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425-478. https://www.doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L. and Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, *17*(5), 328-376. https://www.doi.org/10.17705/1jais.00428

Venkatesh, V., Thong, J. Y. L. & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of acceptance and use technology. *MIS Quarterly*, *36*(1), 157-172. https://www.doi.org/10.2307/41410412

Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1-2), 641-652. https://www.doi.org/10.1007/s10479-020-03918-9

Weerakkody, V., Molnar, A. & El-Haddadeh, R. (2014). Indicators for measuring the success of video usage in public services: The case of education. *20th Americas Conference on Information System* (pp. 1-8). Retrieved from https://bit.ly/3ti2qhV

Williams, M. D., Rana, N. P. & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review. *Journal of Enterprise Information Management*, *28*(3), 443-488. https://www.doi.org/10.1108/JEIM-09-2014-0088

Zhu, G., So, K. K. F. & Hudson, S. (2017). Inside the sharing economy: Understanding consumer motivations behind the adoption of mobile applications. *International Journal of Contemporary Hospitality Management*, *29*(9), 2218-2239. https://www.doi.org/10.1108/IJCHM-09-2016-0496