Identifying relevant segments of AI applications adopters – Expanding the UTAUT2's variables

Juan-Pedro Cabrera-Sánchez
PhD Student
jcabrera10@us.es
Business Administration and Marketing
University of Sevilla, Spain
Ángel F. Villarejo-Ramos
Associate Professor
curro@us.es
Business Administration and Marketing
University of Sevilla, Spain
Francisco Liébana-Cabanillas
Professor
franlieb@ugr.es
Marketing and Market Research Department
University of Granada, Spain
Aijaz A. Shaikh*
Postdoctoral Researcher
aijaz.a.shaikh@jyu.fi
Jyväskylä University School of Business and Economics, P.O.Box 35, FI-40014,
University of Jyväskylä, Finland
* *Corresponding Author*

Abstract

Artificial intelligence (AI) is a future-defining technology, and AI applications are becoming mainstream in the developed world. Many consumers are adopting and using AI-based apps, devices, and services in their everyday lives. However, research examining consumer behavior in using AI apps is scant. We examine critical factors in AI app adoption by extending and validating a well-established unified theory of adoption and use of technology, UTAUT2. We also explore the possibility of unobserved heterogeneity in consumers' behavior, including potentially relevant segments of AI app adopters. To augment the knowledge of end users' engagement and relevant segments, we have added two new antecedent variables into UTAUT2: technology fear and consumer trust. Prediction-orientated segmentation was used on 740 valid responses collected using a pre-tested survey instrument. The results show five segments with different behaviors that were influenced by the variables of the proposed model. Once known, the profiles were used to propose apps to AI developers to improve consumer engagement. The moderating effects of the added variables—technology fear and consumer trust—are also shown. Finally, we discuss the theoretical and managerial implications of our findings and propose priorities for future research.

Keywords: Artificial intelligence; UTAUT2; segmentation; technology fear; consumer trust; heterogeneity

1. Introduction

In recent years, advanced technologies, robotics, expert systems, and artificial intelligence (AI) applications and devices have become integral components of information technology (IT) policies and business strategies. Several developments in different AI-based gadgets have been introduced and deployed during the last decade, including voice recognition systems, virtual assistants, online recommendation systems, chat-bots, self-driving cars, and even search engines. These breakthroughs in AI technologies were, perhaps, due to the digital transformation initiatives undertaken in several countries, including members of the European Union. According to Gabriel and Goertzel (2019), by the end of 2020, the global AI market will exceed 45 billion USD. Considering this exponential growth in the demand for AI technologies, researchers (Sun and Medaglia, 2019) have compared the AI revolution to the industrial and digital revolutions.

Reflecting on the capabilities of AI technologies, researchers (Kaplan and Haenlein, 2019; Duan et al., 2019) have argued that AI is a system or application that is capable of correctly interpreting both internal and external data, learning from such data, and using those learnings to achieve specific individual or organization-wide goals. AI enables greater personalization of information and services by considering a consumer's needs and demands. This helps companies across various sub-sectors of the economy improve their decision-making, problem-solving (Androutsopoulou et al., 2019), customer service, personalization, conversion, and retention. Per prior findings (Waller and Fawcett, 2013), AI and similar technologies allow organizations to obtain and process a great quantity of valuable data in real time and use it to predict, describe, and even prescribe consumer and market behavior. This knowledge allows companies to become leaders and gain competitive advantages (Sivarajah et al., 2016), such as when Google recommends a restaurant nearby or when Booking.com shows consumers hotels in places they plan to visit. These companies are using AI applications to improve customers' experiences and increase engagement.

In addition to immense benefits, several challenges to the AI technologies, devices and services have been reported in the research. One of the major challenges, for example, include the ignorance, technology fear, and consumer distrust (Yaqoob et al., 2016).

With regard to consumer preferences for convenient, innovative products, services, and devices, digital natives (i.e., consumers of the Gen Z and millennial generations) have distorted traditional business models, disrupted several business empires, and created a demand for more innovative, AI application-supported, and shared business models. It is widely believed that Big Data and AI are near ubiquitous (Kaplan and Haenlein, 2019) and they have received significant attention from tech-savvy consumers.

Most previous empirical studies have focused on the technical side of Big Data, AI (Lecun et al., 2015; Triguero et al., 2015), app development, statistical algorithms, data mining cases, and analytics (Sivarajah et al., 2016). The focus of most of these studies is limited to the health and education sectors (Fan et al., 2018; Churamani et al., 2017), social networks (Liu, 2019), and the organizational perspective (Liu et al., 2020). We also found that a few studies have focused on the initial adoption of new and innovative technologies, systems, and applications, including AI, from the consumer perspective. Prior research (Schepman and Rodway, 2020) has argued that consumers' general attitudes toward AI applications and systems likely play a major role in AI's acceptance and prolonged use.

Given the dearth of research examining consumer or end-user behaviors, attitudes, and beliefs toward the adoption and use of AI apps, the purpose of the present work is multi-fold. First, in the context of a developed country, we extend and validate one well-established unified theory of adoption and use of technology model, UTAUT2, that predicts an individual's behavioral intentions and use of information technology, such as AI. Second, we determine the critical factors affecting the adoption and use of AI apps by adapting UTAUT2. Third, we add two new constructs to the UTAUT2, technology fear and consumer trust, as these could influence the individual's behavioral intention to use AI apps. We added these two variables to improve the UTAUT2 and analyzed differences in consumers' behaviors by describing a few segments that explain intention to behave a certain way regarding AI apps. These newly variables will allow us to make recommendations on how to design and promote AI apps. We also propose a segmentation that defines the unobserved heterogeneity of these consumers or end users.

There are diverse papers on segmentation concerning technology adoption in different contexts, such as mobile banking (Shaikh and Karjaluoto, 2015), mobile financial services apps (Karjaluoto et al., 2019), information and communication technology adoption (Fuentes-Blasco et al., 2017), mobile phone use (Rondan-Cataluña et al., 2010), mobile TV versus mobile news apps (Verdegem and De Marez, 2011), and even video games (Ramírez-Correa et al., 2018). However, none were found on a posteriori segmentation related to AI app adoption using latent class segmentation. Finally, we provide further insight into the role that demographic factors, such as age and income, could play in AI app adoption intention and usage.

The ramifications of this study are clear for AI app developers, business executives, and policymakers. For example, it would be meaningful for the practice to know which among the variety of UTAUT2 constructs largely affect consumer intention, use, and success of AI apps. Also, how technology fear and consumer trust moderate the relationship between behavioral intention and use behavior toward the AI apps? Especially as they relate to consumer fear about AI technology and the lack of consumer trust in AI apps, the contributions of this study have important public policy ramifications for consumers' personal data safety and security, particularly given that almost all AI apps communicate with the cloud.

The remainder of this of this paper is as follows: section 2 provides the theoretical background and the state of AI in Spain, the context of the study; section 3 explains the research model and the hypotheses development; section 4 discusses the research methodology; section 5 reports the findings; and section 6 presents the main theoretical and practical conclusions and also the study's limitations.

2. Theoretical background

2.1 Artificial intelligence apps

Mobile application software options for smartphones (apps) have grown enormously since the inception of app markets (Liao et al., 2018). Per Statista's latest report (2018) on the use of mobile apps, more than 45% of participants remembered having between 1 and 15 applications on their smartphone. There are currently many apps available to carry out any type of activity, from solutions for increasing work productivity to help with learning a new language or leading a healthier life. However, the needs of users are changing, and applications for mobile devices are changing (Yen et al., 2019) with more AI options now embedded in various applications. As predicted by Gartner (2019), the exploration and implementation of AI-based applications and systems will rapidly become quite evident, with companies and consumers soon witnessing the presence of AI features in various applications on smart devices.

Currently, the AI apps include voice assistive apps (e.g., Siri, Alexa), which are used in a variety of devices; facial recognition apps (e.g., AppLock, FaceApp), which are commonly used for security purpose such as unlocking phones or to recognize faces in a photo library, online recommendation apps (playlist generators for video and music services (e.g., Netflix, YouTube, and Spotify), which use recommendation algorithms based on permissions and functionalities; and geolocation apps (e.g., Google Maps, Bizzy), which are used to assist people with map navigation and nearby recommendations (Hoy, 2018; Peng et al., 2018; Oikonomidis and Fouskas, 2019).

Different from expert systems, AI developments have been divided into three major eras (See Figure 1). The first era is Artificial Narrow Intelligence (ANI), which is highly predictive, re-active in nature, and based on predefined rules. ANI, which is sometimes referred to as "weak AI" or "special-purpose AI," includes devices and solutions that perform specific tasks (e.g., smartphones are recognizing faces and other biometric features, weather forecasting, etc.). The second era is Artificial General Intelligence, which can sense and solve problems in tasks for which it was never designed (Kaplan and Haenlein, 2019). The third era is Artificial Super Intelligence (ASI), which comes quite close to the true definition and meaning of AI. ASIs are capable of innovative scientific creativity, social skills, and general wisdom (Kaplan and Haenlein, 2019), and they could make humans redundant.

[Insert Figure 1 about here]

2.2 The state of AI in Spain

Many countries are becoming aware of the significance and transformative power of AI for their economies, societies, public services, and labor markets. Consequently, they have increasingly recognized the need for comprehensive national AI strategies. In Spain, this approach is still far from reality. For example, in March 2019, Spain's Ministry of Science and Innovation and universities published one report, titled "RDI Strategy in Artificial Intelligence," setting the priorities for the AI field. These priorities include developing a framework for research, development, and innovation (RDI) in AI; identifying key research and innovation priority areas in AI; facilitating the transfer of knowledge and its return to society; and fostering the development of education and competences in the field of AI.

A recent Organization for Economic Co-operation and Development report indicates that private equity investment in AI-focused startups in Spain from 2011 to mid-2018 represents 3% of the total amount invested in start-ups based in the EU, far behind France (13%), Germany (14%), and the United Kingdom (55%). According to a study carried out by the consulting firm Roland Berger, "Joining the Dots: A Map of Europe's AI Ecosystem," the four most important countries in AI in Europe are the United Kingdom, France, Germany, and Spain. These data show that there is a wide margin for improvement with a better system of cooperation between agents and that the technological investment made so far in Spain is insufficient. Ultimately, without solving these two aspects, Spain will not have an environment that favors AI technologies. In the private sector, AI activity is growing rapidly both through startups and in large companies and multinationals, with initiatives focused on the creation of R&D centers in AI technologies, so it is essential to encourage the analysis, study, and modeling of the factors that analyze the intention to use these tools.

2.3 The UTAUT2 and its constructs

Although the UTAUT model adequately explains companies' adoption of technology, it had to be revised and expanded to explain consumers' adoption of technology, giving rise to the UTAUT2 (Venkatesh et al., 2012). Anecdotal evidence has suggested that the motivations for introducing the UTAUT2 included increased momentum in examining the consumer context due to growing interest in adopting and using new systems and technologies and to account for the latest technological developments. Venkatesh et al. (2012) included hedonic motivation, price-value, and habit in the UTAUT2, which was created to not only analyze IT adoption but also to predict future Use behaviour (Ramírez-Correa et al., 2019). The model comprises seven independent factors that influence the dependent factor behavioral intention, including performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, price-value, and habit.

2.3.1 Behavioral intention

Prior research has examined consumers' behavioral intentions in the context of online banking technology adoption (Guriting and Ndubisi, 2006; Luarn and Lin, 2005). These studies have reported a significant relationship between perceived usefulness/perceived ease of use and behavioral intention. Similarly, perceived playfulness in internet usage (Moon and Kim, 2001) and flow experience in online games (Hsu and Lu, 2004) correlate with behavioral intention. Baumann et al. (2007) took a different approach and segregated behavioral intention between short-term and long-term consumers. Here, a short-term behavioral intention allows a consumer to remain with a specific service provider for one year or less. However, in a long-term behavioral intention, this duration extends for five years or more.

2.3.2 Performance expectancy and effort expectancy

The two key constructs of the UTAUT and its variant the UTAUT2 are performance expectancy and effort expectancy. Influenced by the technology acceptance model (TAM) that was introduced by Davis (1989), Venkatesh et al. (2003) included performance expectancy in place of "perceived usefulness" and effort expectancy in place of "perceived ease of use." In addition, per Venkatesh et al. (2003) and Muhammad et al. (2018), performance expectancy comprises "perceived benefit" and "relative advantage," while effort expectancy is considered similar to "perceived ease of use," "complexity," and "ease of use" (Magsamen-Conrad et al., 2015; Shaikh, 2016; Venkatesh et al., 2003) in influencing user behavioral intentions. In justifying the inclusion of performance expectancy in examining AI adoption, the authors understand that, until AI applications are fully developed and deployed, it will be difficult to predict their performance or usefulness. Moreover, it is widely believed that AI-based applications have better performance compared to other online applications.

Previous studies (Ramírez-Correa et al., 2019; Venkatesh et al., 2003) have defined effort expectancy as the degree of ease that is associated with an individual's use of a technology or an information system. Therefore, the perceived ease of use of an information system or technology assumes that such ease is more likely to induce behavioral intention and that effort expectancy has a significant influence on behavioral intention (Casey and Wilson-Evered, 2012). For example, in the context of mobile banking, Alalwan et al. (2017) found that EE significantly and positively influenced behavioral intention.

2.3.3 Social influence

With modern society always connected via various technologies, including social media, the interactions both between and among individuals and communities have increased tremendously and subsequently created a social atmosphere that has increased customer awareness and influenced the choices, intentions, and attitudes of individuals. This social atmosphere consists of reference groups, family and friends, colleagues, etc. According to Venkatesh et al. (2003), social influence is the extent to which a person perceives that others believe that it is important for him/her to apply a new information system or technology. Prior research has examined social influence in a variety of contexts, and its relationship with behavioral intention has been reported as both significant and insignificant. For example, in the context of mobile banking services, the relationship between social influence and behavioral intention was reported as insignificant (Alalwan et al., 2017; Merhi et al., 2019).

2.3.4 Hedonic motivations

Several features are usually embedded into information systems and applications to increase consumer engagement, adoption, and usage, and they are broadly categorized under two major domains. The first domain includes productivity-oriented features that provide utilitarian or instrumental value to consumers and users. These productivity-oriented features, as explained by Van der Heijden (2004), promote extrinsic motivation, which demands rewards or external benefits. Popular examples of constructors that drive extrinsic motivation among users include perceived usefulness (or performance expectancy).

The second category includes pleasure-oriented features that provide hedonic or self-fulfilling value to consumers and users of systems and applications. Per Van der Heijden (2004), hedonic features are strongly connected to family, home, and leisure activities and thereby target pleasure, happiness, and the fun aspect of using information systems or applications. The underlying purpose of embedding these hedonic features is to encourage the sustained or continuous usage of the application or system. Hedonic or self-fulfilling value promotes intrinsic motivation. Popular examples of the constructs that drive intrinsic motivation include hedonic expectancy, perceived enjoyment, flow experience, and perceived playfulness.

Per Tamilmani et al. (2019, p. 223), hedonic motivation is the “fun or pleasure derived from using a technology or system, and it is an important determinant of a consumer’s technology acceptance and sustained use.” Prior research has found significant correlations between hedonic value and the Use behaviours of the mobile internet (Park, 2006) and mobile social network games (Paavilainen et al., 2012). Enjoyment has also been found to have a key role in virtual reality tourism (Tussyadiah et al., 2018).

2.3.5 Price-value

Price-value is an individual’s cognitive trade-off between the perceived benefits of the applications and the monetary cost that is connected with using them (Ramírez-Correa et al., 2019). The benefits that drive price-value include convenience, quality, comfort, and ubiquity. The sacrifice is the monetary cost as well as the usage fees (if any) and the perceived risk of or actual privacy loss that is associated with using an application or system (Shaw and Sergueeva, 2019). Notably, some authors (e.g., Herrero and San Martín, 2019; Shaw and Sergueeva, 2019) have substituted price-value with perceived value (context: mobile commerce), privacy concerns (context: social network sites), etc.

2.3.6 Habit

Habit is another factor that is considered significant to behavioral intention. Research has found that habitual behavior largely plays a role in the context of extended, sustained, or continuous usage of an information system. In the context of information system usage, Limayem et al. (2007) defined habit as the extent to which consumers tend to perform behaviors automatically and repeatedly because of learning. Although sufficient evidence (e.g., Ramírez-Correa et al., 2019) is available to suggest that habit is correlated with behavioral intention, a key question remains: What factors develop habit or the habitual behavior of a consumer? Per Limayem et al. (2007), the answer is consumer satisfaction, frequency of past behavior, and comprehensiveness of usage.

2.3.7 Facilitating conditions

Shaw and Sergueeva (2019) defined facilitating conditions as the conceptualized knowledge, resources, and opportunities that are required to perform a specific behavior. Certain conditions as well as resources are required to facilitate the adoption and usage of an information system to complete a task. Developed countries have stable facilitating conditions, such as advanced telecommunication infrastructures, broadband and stable internet connectivity, and advanced education systems. These conditions allow greater adoption and usage of information systems and facilitating conditions; therefore, they are considered a significant predictor of the behavioral intention to use an information system. Prior research has examined facilitating conditions in a variety of contexts. For example, facilitating conditions can positively predict tablet use intentions (Magsamen-Conrad et al., 2015) and directly influence mobile banking adoption (Oliveira et al., 2014).

3. Research model and hypothesis development

As a synthesis of previous models such as TAM (Davis, 1985), TPB (Ajzen, 1991) or TRA (Fishbein & Ajzen, 1975), we consider the UTAUT model (Venkatesh et al., 2003) one of the most suitable for measuring the acceptance level and use of tools that have been developed through AI. However, while the UTAUT focuses on companies, the UTAUT2 (Venkatesh et al., 2012) is orientated toward explaining the acceptance and use of technologies by end users. Therefore, this model will help us understand how end users adopt and use AI apps in a developed country. In addition to traditional UTAUT 2 constructs, in this research, we have used two new latent variables, technology fear and consumer trust, to assist in finding new clusters based on end-consumer behavior. This conceptual model is depicted in Figure 2.

[Insert Figure 2 about here]

3.1 Performance expectancy on behavioral intention

Performance expectancy is one of the most influential constructs in terms of behavioral intention. In addition to Venkatesh et al. (2003), several other authors have also established a relationship between performance expectancy behavioral intention. For example, in the mobile banking context, Merhi et al. (2019) found that performance expectancy is an influential predictor of a consumer's behavioral intention, while Chauhan et al. (2018) found similar results regarding voting machines,and Mosunmola et al. (2019) studied this phenomenon in mobile learning. However, this effect was insignificant in the use of online games on mobile devices (Ramírez-Correa et al., 2019). Therefore, we propose the following hypothesis:

H1: Performance expectancy is positively related to behavioral intention.

3.2 Effort expectancy on behavioral intention

Like performance expectancy, the relationship between effort expectancy and behavioral intention is well established. Several studies (e.g., Al-Gahtani et al., 2007; Chauhan and Jaiswal, 2016; Kim et al., 2007; Lee and Song, 2013; Yu, 2012) have reinforced the sense and weight of the effect that effort expectancy has on behavioral intention. In the context of mobile technology, multiple studies have verified that behavioral intention is significantly and positively influenced by effort expectancy, including mobile banks (Alalwan et al., 2017), mobile cloud services (Park and Kim, 2014), mobile maps (Park and Ohm, 2014), mobile Short Message Services (Beza et al., 2018), and mobile learning (Ho et al., 2010). Thus, the following is hypothesized:

H2: Effort expectancy is positively related to behavioral intention.

3.3 Social influence on behavioral intention

Social influence is used to measure the effect of what others think about the use of a technology or system (Venkatesh et al., 2003). Some recent studies have described social influence as a strong antecedent of the behavioral intention to use (Arenas-Gaitán et al., 2019; Dwivedi et al., 2019; Merhi et al., 2019; Sharif et al., 2019). Therefore, we hypothesize the following:

H3: Social influence is positively related to behavioral intention

3.4 Hedonic motivations on behavioral intention

Hedonic motivations are the pleasure and/or the enjoyment that is obtained with the use of technology (Venkatesh et al., 2012). Prior research (Brown and Venkatesh, 2005; Nysveen, 2005; Van der Heijden, 2004) has established that hedonic elements, such as enjoyment, are important antecedents of consumers behavioral intention to use new and emerging technology, such as AI apps. Studies in the areas of touristic geolocation (Gupta and Dogra, 2017), mobile commerce (Zhang et al., 2012), and omnichannel commerce (Juaneda-Ayensa et al., 2016) have considered hedonic motivation one of the most important antecedents of the behavioral intention to use new technology by end users. Therefore, the following is hypothesized:

H4: Hedonic motivation is positively related to behavioral intention

3.5 Price-value on behavioral intention

Considering consumers' growing intent to adopt and use new systems and technologies, Venkatesh et al. (2012) introduced the UTAUT2 and added contextual factors, such as price-value and habit. Price-value replaces perceived value and explains, compares, and represents a cognitive trade-off between the cost of using an IT artefact vs. the benefit of using an IT artefact. Examining the relationship between price-value and behavioral intention in the context of internet banking technologies (Alalwan et al., 2018) and in the mobile context (Ameen et al., 2018), authors found that behavioral intention is significantly influenced by price-value. Therefore, we proposed the following hypothesis:

H5: Price-value is positively related to behavioral intention.

3.6 Habit on behavioral intention and use behavior

Habit is considered automated conduct based on learnt behavior (Ameen et al., 2018; Limayem et al., 2007). When the UTAUT2 model was originally presented, Venkatesh et al. (2012) showed that habit resulted from previous experiences as well as how such experiences can motivate the use of new technologies (Ajzen, 2002). Subsequent studies have shown the influence of habit on the behavioral intention to use a new technology (Kim et al., 2008; Merhi et al., 2018; Wu and Kuo, 2008). Habit not only affect behavioral intention but also prolong use (Ameen et al., 2018; Gupta and Dogra, 2017; Limayem et al., 2007; Tamilmani et al., 2018). Thus, the following is hypothesized:

H6a: Habit is positively related to behavioral intention.
H6b: Habit is positively related to use behavior.

3.7 Facilitating conditions on behavioral intention and use behavior

Facilitation or facilitating conditions imply the availability of the necessary infrastructure to facilitate access as well as the use of available technologies, channels, and devices in the everyday lives of consumers. Here, the UTAUT has explained that facilitating conditions influence behavioral intention and Use behavior (Venkatesh et al., 2003). Contemporary research findings have also verified a positive relationship between the facilitating conditions and behavioral intention (Duyck et al., 2010; Holzmann et al., 2018; Morosan and DeFranco, 2016). For example, while examining consumers' intentions to use NFC mobile payments in hotels, Morosan and DeFranco (2016) found a direct relationship between facilitating conditions and behavioral intentions. Similarly, research (Al-Gahtani et al., 2007; Chauhan and Jaiswal, 2016; Duyck et al., 2010; Gharaibeh et al., 2018; Kim et al., 2007) has a found direct relationship between the facilitating conditions and the use of a new technology. Thus:

H7a: Facilitating conditions are positively related to behavioral intention.
H7b: Facilitating conditions are positively related to use behavior.

3.8 Technology fear and consumer trust on behavioral intention

The technology fear stems from technology anxiety (Guo et al., 2013; Niemelä-Nyrhinen, 2007; Venkatesh, 2000), from which we know that the more novel the technology is, the greater is the anxiety. The inhibitor effect of fear is especially relevant in behavioral intention when the user has not used the technology previously (Gelbrich and Sattler, 2014). The fear of the consequences of using a new technology causes a break in behavioral intention, which causes insecurity and a feeling of intimidation. Furthermore, fear is an important obstacle for the intention to use, as Heinssen Jr. et al. (1987) found with the Computer Anxiety Rating Scale in the dimension of denominated fear. Therefore, we have hypothesized the following:

H8: Technology fear is negatively related to behavioral intention.

By contrast, trust in consumer reflects the security of the end user regarding expectations of the other side of the relationship (Schoorman et al., 2007). The user expects a high level of ability from the e-services provider in task performance, compliance with the service promise, and benevolence in user profit (Wu and Chen, 2005). Trust has been one of the stronger predictors of the behavioral intention of e-commerce (Bock et al., 2005). As Zhou (2012) indicated, consumer trust in a technological system can positively and directly affect behavioral intention because the user hopes to obtain a profit with the use of this technology. Therefore, we have hypothesized the following:

H9: Consumer trust in positively related to behavioral intention.

3.9 Behavioral intention on use behavior

Several technology acceptance and usage models have been introduced in the past, such as the TAM (Davis, 1989) and its modifications and the UTAUT (Venkatesh et al., 2003) and its modifications, which have established a positive relationship between behavioral intention and Use behaviour. This relationship has been verified in many environments that are similar to AI app adoption and use, such as internet banking adoption (Martins et al., 2014), a multi-modal avatar-based tool (García et al., 2019), online games in mobile devices (Ramírez-Correa et al., 2019), and ERP adoption (Chauhan and Jaiswal, 2016). Accordingly, we propose the following hypothesis:

H10: Behavioral intention is positively related to use behavior.

3.10 Moderating effect of technology fear and consumer trust

Despite consumers' widespread use of technology in their everyday lives, the fear of technology, also referred to as "technophobia" and "technology avoidance," remains a significant problem among most of the population worldwide. Different from computer or IT anxiety, we consider technology fear close to technophobia and categorize it within a broader concept that includes aversive behavioral, affective, and attitudinal responses to new technologies, systems, and smart devices (Martínez-Córcoles et al., 2017).

Similarly, the adoption of new or modern technologies or systems is largely influenced by technology fear and discomfort (Martínez-Córcoles et al., 2017). This is largely because the mindset and culture of the consumer is not cultivated to take unforced risks while investing in new technologies and systems with the underlying purpose of accomplishing tasks. Resultantly, unless a technology reaches the mainstream (for example, an AI app or device controls heating and lighting at your office and home), its diffusion among most consumers will remain low. Moreover, according to Khasawneh (2018), the proliferation of new technologies and systems pressures consumers to adopt new technologies within a short period, which incites emotional and cognitive reactions and fear among consumers. As a result, the intentions and use behavior of the consumer remain suspicious of new technologies, systems, or devices.

It is possible that higher technology fear among consumers could distort the relationship between behavioral intention and use behavior regarding AI apps. The moderating effect of technology fear on behavioral intention in explaining the use behavior may be weaker for AI app users with high technology fear. Given this situation, we expect that behavioral intention is less important in explaining use behavior when technology fear among consumers is substantial. Thus, we hypothesized the following:

H11a: Technology fear will moderate the effects of behavioral intention on use behavior such that it will be weaker among AI app users with high technology fear.

Consumer trust is defined as the "willingness to rely on an exchange partner in whom one has confidence" (Moorman et al., 1993, p. 82). Consumer trust in a technology, system, or brand is widely considered one of the key elements of effective working relationships between consumers and businesses, generating commitment that leads to strong, long-term relationships (Sharma and Klein, 2020) and use behavior. Consumer trust is paramount in developing and retaining consumer satisfaction, loyalty, a sustainable competitive advantage, and increased revenue (Sharma and Klein, 2020).

Earlier, some significant direct relationships between trust and behavioral intention (Alalwan et al., 2017), trust and attitude (Muñoz-Leiva et al., 2017), and trust and usage intention (Zhou, 2012) were found and reported in prior research. In this study, we have conceptualized trust as a potential moderating variable that affects one important structural link in the model (behavioral intention and use behavior). With regard to the usage behavior, we argue that consumer trust plays a decisive role, buffers the effects of negative consumer intentions, and decreases consumer churn. The moderating effect of consumer trust on behavioral intention in explaining use behavior is higher for AI app users with high trust. We therefore hypothesized the following:

H11b: Consumer trust will moderate the effects of behavioral intention on use behavior such that consumer trust will be strong among the AI app users with high trust.

4. Research methodology

4.1. Survey development

The conceptual model included 11 latent variables (see Annex I). In all cases, a seven-point Likert scale was used to measure multiple items from 1 (strongly disagree) to 7 (strongly agree). All the items were adapted from the literature to preserve content validity (Straub et al., 2004). For example, the scales were adapted from Venkatesh et al.'s (2003) original UTAUT model, the extended UTAUT2 model (Venkatesh et al., 2012), and Davis's (1989) TAM. The scale items were adapted to geolocation maps, recommendation systems in e-commerce, and voice recognition as applications of AI for testing in our research. The measurement scales for the new variables that were proposed for clustering—technology fear and consumer trust—were adapted from Heinssen et al. (1987) and Pavlou and Gefen (2004), respectively.

The survey had three parts. The first part contained a validation clause to make sure that the respondents had at least a basic understanding of AI apps and their usage. The second part contained the demographic profile of the respondents. The third and final section contained the items list. The survey was pre-tested on a group of students and researchers at a local university. The wording of the items was modified to suit this study based on the feedback received from this pilot test.

4.2 Sample description

The non-probabilistic sample that was used in this research came from people in Spain who responded to a self-administered questionnaire that was published on online social networks. The data were collected during March 2018. Previously, several users and expert researchers carried out a preliminary test of this questionnaire. In total, 780 people responded. After initial scrutiny of the survey instruments, 40 responses were rejected for being incomplete or presenting inconsistencies in the responses. The remaining 740 responses were considered and analyzed. These responses spanned various regions and areas in Spain.

The analysis of socio-demographic variables in the sample indicated that 49.86% were female, the average age was 27.9 years old, and 71.2% were single. Most of the sample (55.3%) had finished secondary studies, and most were current university students; notably, 43.4% were university graduates. Only 22.4 % were hired workers, and 65.8% were students. Finally, 67% lived in a home with a monthly income > 1,500 €.

4.3 Statistical tools

The present study utilized a Partial Least Squares (PLS) method (Chin and Dibbern, 2010; Hair et al., 2012) to test the structural model and both the validity and the reliability of the scales, which measured the different items and their relationships. The SmartPLS 3.2.3 software suite performed all necessary calculations (Ringle et al., 2015).

Complying with the recommendations of Kock (2015) and Kock and Lynn (2012), this research previously recognized the absence of measurement bias error and common method bias (CMB). In this regard, the questionnaire presented respondents with several questions that were detached from the structural model and unrelated to the research at hand. The procedure involved a latent variable that was dependent on the other variables in the model. This new variable (CMB) approached the variables as potential antecedents and included the necessary indicators. In this regard, variance inflation factors needed to yield a value lower than 3.3 to ensure that the sample was not influenced by CMB. Table 1 shows that the obtained values for every construct in the model were within the recommended threshold.

[Insert Table 1 about here]

5. Findings

5.1. Measurement model

The research process followed two steps: 1) We contrasted the hypotheses of the causal model that was posed by PLS and 2) tested latent class segmentation with PLS-Predicted-Orientation Segmentation (POS) by incorporating the two variables that were relative to the engagement level shown in the sample regarding possible heterogeneous behavior. In the first step, to test the reliability and validity of the measurement model, we reviewed the current literature (Henseler et al., 2014; Roldán and Sánchez-Franco, 2012), which states that the loadings of every construct should be above 0.7, and ensured that the loadings met the requirement. We then analyzed the reliability of the constructs with the help of composite reliability indicators and Cronbach's Alpha. In all circumstances, the values of our indicators were above 0.7 as proposed by Nunnally (1978). We also guaranteed that there was convergent validity by examining the average variance extracted. In this case, all values were greater than 0.5, as proposed by Straub et al. (2004) (Table 2).

[Insert Table 2 about here]

Finally, we assessed the discriminant validity of the measurement model by using the restrictive method of the Heterotrait-Monotrait ratio (Henseler et al., 2014) to ensure that all values were below 0.9 (Table 3). We can see the R2 of the second order constructs BI and UB (Table 4).

[Insert Table 3 about here]
[Insert Table 4 about here]

5.2 Structural model assessment

In our proposed conceptual model depicted in Figure 2, we hypothesized structural relationships between behavioral intention and its antecedents: performance/effort expectancy, social influence, hedonic motivations, price-value, habit, facilitating conditions, technology fear, and consumer trust. We also hypothesized the structural relationships between behavioral intention and use behavior. The path coefficients reflect the strength of the relationship between dependent and independent variables. In order to calculate these coefficients, we carried out a bootstrapping technique with 10,000 sub-samples to find the reliability of the path coefficients in the hypothesized relationships (see Table 5).

[Insert Table 5 about here]

To assess the model's goodness of fit, we used the Standardized Root Mean Square Residual (SRMS) criterion. The value obtained was 0.052, which fell below the 0.08 value that Henseler et al. (2014) proposed. Therefore, we can accept all proposed hypotheses (except H7a) and state that the complete model has a good fit. The model has an explanatory power of 17.9% in use behavior and 46.7% in behavioral intention (Table 4), which are above the minimum threshold of 10% suggested by Falk and Miller (1992). These values may increase significantly once we identify the heterogeneity in technology adoption among end users or consumers. Once we determined that the model is valid and consistent, we used it as a basis for finding different clusters of end users.

We checked the moderating effects of gender, income, technology fear, and consumer trust. We found that gender and income significantly affect the relationship between facilitating conditions and use behavior (Table 6) and hedonic motivations and behavioral intention (Table 7), respectively. Trust and technology fear moderate the relationship between behavioral intention and use behavior (Table 8).

[Insert Table 6 about here]
[Insert Table 7 about here]
[Insert Table 8 about here]

As a second step, we performed a PLS-POS latent class segmentation by following the instructions proposed by Becker et al. (2013), from which we obtained five different end-user (or consumer) segments. To do so, we followed the criterion of the mean of the explained variance of the proposed mode. As can be seen in Table 9, we reached the highest R2 with five segments (in bold).

[Insert Table 9 about here]

An error was produced when some segments contained fewer than eight units, which indicated a lack of significance (Becker et al., 2013). Finally, the assessment of the structural model for all the segments was approached. The path coefficients and the p-values are shown in Table 10, with the size of each segment in brackets and all significant relationships in bold.

The explained variance (R2) of the endogenous variables are shown in Table 11. We can see the increase of the explicative power of the model in each segment in Tables 9 and 11 for BI and UB.

[Insert Table 10 about here]
[Insert Table 11 about here]

5.3. Segmentation related to AI adoption using latent class segmentation

The UTAUT2's variables and the socio-demographic variables, such as gender, age, registration of place of residence, civil status, household income, level of studies, and employment status, were assessed to describe the five segments that were approached in the present study. Two of the previously discussed variables were also examined: technology fear and consumer trust. We wanted to determine whether any of these variables were significantly different in one or more of the five segments. Therefore, we performed an analysis of variance (ANOVA) and found no significant differences in any socio-demographic variables of the UATUT2 model. In the case of behavioral intention, effort expectancy, hedonic motivation, price-value, and the newly included variables technology fear and consumer trust affected the different segments (see the results in Table 12). Only these variables (in bold) had significant differences between the segments.

[Insert Table 12 about here]

We also performed a Chi-square test to search for any relation between the categorical socio-demographic variables (gender, city of residence, kind of job, civil status, studies, and familial income) and the different segments, with no association found. Because all the tests were negative, we can conclude that none of the socio-demographic variables affects the segments that were obtained.

6. Discussion, implications, and limitations

Using the UTAUT2 model, this article examines the factors that affect AI adoption among a heterogeneous group of people in Spain. This study offers important contributions in the context of AI application adoption, such as that behavioral intention yields the strongest effects on consumer use behavior and that performance expectancy and hedonic motivation have the greatest influence on behavioral intention.

6.1 Theoretical Implications

Our findings provide some useful theoretical contributions. For example, our research shows that the revised and extended UTAUT2 model is consistent and that the behavioral intention toward AI apps is positively and significantly influenced by certain variables, notably performance expectancy and hedonic motivations. The perception of how AI applications are useful (performance expectancy) in achieving in day-to-day objectives is in line with the earlier findings reported by Lee and Song (2013) on e-governments and by Yu (2012) on the behavioral intention to use internet banking. The positive influence of hedonic motivation on using AI apps follows studies in the same context of online purchasing (Chen and Zhang, 2014) and in tourist recommendations for online reservations (Gupta and Dogra, 2017). Regarding the remaining variables of the original UTAUT2 model, we highlight a relevant influence (although at a lower level of demand) on the behavioral intention to use AI apps: The effort expectancy (the AI application's ease of use) is in line with the findings of Cabrera-Sánchez and Villarejo-Ramos (2018) as are the social influence (what others consider appropriate to use), the perceived price-value (the value that end users associate with cost), and habit, as measured by the habitual use of these systems. The facilitating conditions (ease of access to the application) do not have a significant influence on behavioral intention, although they do on use behavior, for which habit also shows a significant favorable effect.

One of the significant theoretical findings of our study is that the extension of the model proposed with two new variables (technology fear and consumer trust) has been significant improving the results of the original UTAUT2 model and supports the results as earlier reported by Wang & Jeong (2018), Wang et al. (2019), and Zhou (2012). The results of this research show that the new variables that were proposed to cluster end users had significance. These variables, although antecedents of use intention of use, indirectly affect use: they have a mediating effect on the relationship between behavioral intention and use behavior. In this sense, those users who have technology fear will reduce their use behavior due to negative perceptions of the technology itself. However, if AI apps users have more confidence, they will increase their use behavior, believing that these systems have numerous advantages. Therefore, technology fear and consumer trust are useful for explaining the unobserved heterogeneity of end users. Some literature exists about a posteriori segmentation with the UTAUT (Ramírez-Correa et al., 2018), but none exists for the UTAUT2. Even with this complex model (the UTAUT is more parsimonious than the UTAUT2), we were able to run a POS-PLS segmentation. After analyzing all data, we discovered great improvement in the explained variance in the endogenous variables. The original model had an explained variance of use behavior of 0.454, and the model with five segments improved this explained variance to 0.735. Same goes with the usage behavior: the original model had an explained variance of 0.178, while the model with five segments reached 0.602. See Table 9.

From the ANOVA (Table 12), only the variables effort expectancy, hedonic motivation, price-value, technology fear, consumer trust, and behavioral intention showed significant differences for the five segments of end users. Table 13 briefly analyzes each segment, which are described below.

The segment-1 (Players): This segment is the smallest (3.78%). The players have the largest value of hedonic motivation, the second largest value of trust, and the smallest value of technology fear, while the rest of the variables have small values. Therefore, we can conclude that those in this segment know the technology, trust it, and enjoy playing with it (although they do not have a significant intention to use it).

The segment-2 (Home end users): This segment is the second largest (28.51%). They have small values for almost every variable, with the exceptions of hedonic motivation and behavioral intention. They think that these apps are not worth the price offered. Those in this segment are not afraid of this technology and even trust it; therefore, they have the highest behavioral intention to use it. They use it for some enjoyment, with a bit of trust and with no fear, but they are not going to pay for it.

The segment-3 (Reluctant): This segment has a medium size (21.08%). They have the smallest behavioral intention of any segment, the largest technology fear, and almost no trust in this new technology. They also think that it is difficult to use and that there is no pleasure in doing it. They are not going to use this technology (at least not in the short term) because they do not trust it.

The segment-4 (Professional end users): This segment is the largest (35.54%), and its users are ready to pay for these apps if they are perceived as worth the cost. They have the largest perceived price-value and a large behavioral intention. They also trust the technology, and they are not afraid of these apps. They enjoy them a bit less than those in Segment 2, but they differ in that they are willing to pay if the app is good. They also see this technology as being very easy to use, which makes them willing to use it.

The segment-5 (Skeptical users): This segment is the second smallest (11.08%). They think that this new technology is very difficult to use (the biggest effort expectancy) and has no hedonic motivation, no price-value, no technology fear (the smallest one), and they fear this technology. Even with these characteristics, they have a greater behavioral intention than Segment 3, although it is not significant. They will use this new technology voluntarily in the short term, but they may use it in the future.

[Insert Table 13 about here]

6.2 Managerial Implications

AI apps, devices, wearables, and sensors are on our wrists, in our pockets, in our homes, in our cars, and in our workplaces, and they are already making a real difference to how we experience life and the world around us (Arm, 2020). This study used the revised UTAUT2 model to explore the acceptance and use of AI apps among a set of consumers and professionals using various AI apps in their daily routines. The UTAUT2 variables were combined with two new variables (technology fear and consumer trust) to create a consistent model for finding different segments of consumers or end users. With the profiles of these groups known, we can make recommendations to app developers, business executives, and policymakers.

6.2.1 For AI app developers

For segment 1 (Players), developers may need to spend more resources to develop and deploy intuitive, simple, and enjoyable AI apps that consumers can access and use frequently. The developers should also make AI apps more useful for specific tasks, no matter the complexity of the programming, and communicate the usefulness or performance expectancy of AI apps to end users. For segment 2 (Home end users), app developers should communicate to the consumers and prospects that AI apps are valuable by explaining their benefits, including their 24/7/365 availability and noticeable time and money savings. Developers should present the AI apps' capabilities for different tasks, increase consumers' trust, and remove fears, such as the fear of privacy intrusion, as in the case of Alexa, a popular virtual/voice assistant developed by Amazon. After all, consumers are trading privacy for convenience.

After the promulgation of consumer privacy regulations such as the General Data Protection Regulation (GDPR), consumer awareness of the amount of their personal data that AI apps and devices need to perform well has grown, and so has demand for security (Arm, 2020). For segment 3 (Reluctant), AI app developers should promote safety and trust in the acquisition and use of AI apps, devices, and services among various consumer segments and prospects interested in acquiring and using the AI apps, devices, and services. For segment 4 (Professional end users), not all AI apps, devices, and services are created equal. Various tendencies were found when choosing and using the AI apps to complete various personal and professional tasks. With this in mind, AI app developers should create apps that help users in their professional tasks and reflect benefits for their professional performance. Finally, for segment 5 (Skeptical users), app developers should promote safety and trust in the acquisition and use of AI apps and communicate the usefulness of these apps, including their ability to save time and money. Messages for this segment should be utilitarian.

6.2.2. For the business executives and policy makers

Respondents placed greater emphasis on the usefulness of AI apps, the hedonic features, and habit. In addition, technology fear and consumer trust play significant roles in developing consumer behavioral intent to use AI apps. These findings provide significant business and marketing guidance to companies developing and deploying AI apps and other technologies. For example, the practice should take greater caution when offering AI apps, considering the growing privacy laws, such as GDPR. The storage and retrieval of private consumer data and how the personal consumer data is processed should be explicit and shared with the consumers. This would reduce the technology fear among consumers and increase their trust in AI apps. More than a third of respondents said they would switch to a competitor's product should an AI device they use be hacked, and another third would consider stopping using that device category altogether. Clearly, the development of AI apps must be supported with an effective marketing communication strategy.

Hedonic features in AI apps are significant. Consumers expect fun and entertainment when using AI-supported devices, apps, and other services. For example, issuing commands, asking questions, and getting a reply or the required information increase hedonic feelings and make a technology feel more intelligent. AI apps that do not create a hedonic experience will make the technology less attractive and ultimately fail. According to Arm (2020), consumers do not feel comfortable when AI apps are either too autonomous or too dictatorial. To make consumers happy, apps should be neither too independent nor too manipulative, but just right.

The industry and consumers have been galvanized by the disruptive challenges created by COVID-19. Out of these crises, a new consumer segment called Generation N has emerged. According to Solis (2020), members of Generation N, or Novel, are tech-savvy digital-centric consumers who have emerged from the fear and anxiety created by the novel coronavirus. Companies and business and marketing executives must prioritize studying and understanding the behavior of Gen N, which is poised to increase exponentially, as the pandemic has accelerated digital behavior among those consumers and prospects who were previously either slow or unmotivated to adopt and use digital products and services.

Moreover, the current pandemic has created complex challenges and uncertainties for businesses and government organizations, including regulators and policymakers. AI apps could play a greater role, and AI-based technology and business models could provide products and services in new contactless ways. Regulators and policymakers should also address their citizens' growing concerns, fear, and lack of trust in AI apps. According to the IFC (2020), a sister organization of the World Bank, policymakers and regulators should take necessary steps to mitigate these concerns, promote responsible stewardship of AI apps, and develop good practices, especially with regard to data protection.

6.3 Limitations and future research directions

Future research should address some limitations associated with the present study. For example, first, only including two variables when expanding the UTAUT2 model (or in this case, to help us segment the database) could have caused bias because the effect of other possible constructs, such as perceived risk, resistance to use, or the conditions of privacy, were not considered. Second, it seems necessary to explore new moderator variables other than those of the original UTAUT2 not only to expand the model but also to help segmentations, with the purpose of evaluating possible new effects not previously contemplated. New moderators can enable us to establish differences in the behavior of consumers and set up possible new market segments. Third, although the observations were collected via online questionnaires, we could not avoid the biases of age (very young) and educational level (mostly university students). Fourth, the use of AI apps is evident in developed countries and slowly gaining popularity in emerging and developing countries as well. Future research may include empirical studies in emerging country contexts and cross-country assessments comparing developed countries with emerging countries. This would provide new insights into consumer behavioral intentions and usage behavior concerning AI apps, devices, and services. Fifth, COVID-19 and other health crises have disrupted many industries and services. Future research should examine how AI could play a role in mitigating these challenges and bringing the world back to normal, especially when there is no pandemic playbook to follow.

References

Ajzen, I., 1991. The theory of planned behavior. Orgnizational Behavior and Human Decision Processes, 50, 179–211.

Ajzen, I., 2002. Residual Effects of Past on Later Behavior. Personality and Social Psychology Review, 6 (2), 107–122.

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., 2017. Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. International Journal of Information Management, 37 (3), 99–110.

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., and Algharabat, R., 2018. Examining factors influencing Jordanian customers' intentions and adoption of internet banking: Extending UTAUT2 with risk. Journal of Retailing and Consumer Services, 40, 125–138.

Al-Gahtani, S. S., Hubona, G. S., and Wang, J., 2007. Information technology (IT) in Saudi Arabia: Culture and the acceptance and use of IT. Information and Management, 44 (8), 681–691.

Ameen, N., Willis, R., Shah, M. H., 2018. An examination of the gender gap in smartphone adoption and use in Arab countries: A cross-national study. Computers in Human Behavior, 89, 148–162.

Androutsopoulou, A., Karacapilidis, N., Loukis, E., Charalabidis, Y., 2019. Transforming the communication between citizens and government through AI-guided chatbots. Government Information Quarterly, 36 (2), 358–367.

Arenas-Gaitán, J., Villarejo-Ramos, Á.F., Peral-Peral, B., 2019. A posteriori segmentation of elderly internet users: Appling PLS-POS. Marketing Intelligence and Planning, 38 (3), 340-353. https://doi.org/10.1108/MIP-01-2019-0057.

Arm, 2020. AI today, AI tomorrow. Retrieved on September 15, 2020 from https://www.arm.com/resources/report/ai-today-ai-tomorrow.

Baumann, C., Burton, S., Elliott, G., Kehr, H. M., 2007. Prediction of attitude and behavioural intentions in retail banking. International Journal of Bank Marketing, 25 (2), 102–116.

Becker, J.-M., Rai, A., Ringle, C. M., Völckner, F., 2013. Discovering Unobserved Heterogeneity in Structural Equation Models to Avert Validity Threats. MIS Quarterly, 37 (3), 665–694.

Beza, E., Reidsma, P., Poortvliet, P. M., Belay, M. M., Bijen, B. S., Kooistra, L., 2018. Exploring farmers' intentions to adopt mobile Short Message Service (SMS) for citizen science in agriculture. Computers and Electronics in Agriculture, 151, 295–310.

Bock, G.-W., Zmud, R. W., Kim, Y.-G., Lee, J.-N., 2005. Behavioral Intention Formation in Knowledge Sharing : Examining the Roles of Extrinsic Motivators. Social-Psychological Forces, and Organizational Climate, 29 (1), 87–111.

Brown, S. Venkatesh, V., 2005. Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle. MIS Quarterly, 29 (3), 399–436.

Cabrera-Sánchez, J.-P., Villarejo-Ramos, Á.F., 2018. Extendiendo el Modelo UTAUT para evaluar los factores que afectan la adopción del Big Data en empresas españolas. En J.A. Trespalacios, R. Vázquez, E. Estrada y C. González (Coord.) Nuevos horizontes del marketing y de la distribución comercial. Ed. Cátedra Fundación Ramón Areces de Distribución Comercial, (pp.181–200).

Casey, T., Wilson-Evered, E., 2012. Predicting uptake of technology innovations in online family dispute resolution services: An application and extension of the UTAUT. Computers in Human Behavior, 28 (6), 2034–2045.

Chauhan, S., Jaiswal, M., 2016. Determinants of acceptance of ERP software training in business schools: Empirical investigation using UTAUT model. International Journal of Management Education, 14 (3), 248–262.

Chauhan, S., Jaiswal, M., Kar, A. K., 2018. The acceptance of electronic voting machines in India: a UTAUT approach. Electronic Government, an International Journal, 14 (3), 255–275.

Chin, W. W., Dibbern, J., 2010. An Introduction to a Permutation Based Procedure for Multi-Group PLS Analysis: Results of Tests of Differences on Simulated Data and a Cross Cultural Analysis of the Sourcing of Information System Services Between Germany and the USA. In V. E. Vinzi, W. Chin, J. Henseler, H. Wang (eds.) Handbook of Partial Least Squares. Concepts, Methods and Applications. Springer, (pp.171–193).

Churamani, N., Anton, P., Brügger, M., Fließwasser, E., Hummel, T., Mayer, J., … Wermter, S., 2017. The Impact of Personalisation on Human-Robot Interaction in Learning Scenarios. Proceedings of the Fifth International Conference on Human Agent Interaction (HAI), accepted.

Davis, F., 1985. A Technology Acceptance Model for Empirically Testing New End-User Information Systems. Massachusetts Institute of Technology, (December 1985), 291.

Davis, F., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13 (3), 319–340.

Duan, Y., Edwards, J. S., Dwivedi, Y. K., 2019. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International Journal of Information Management, 48, 63–71.

Duyck, P., Pynoo, B., Devolder, P., Voet, T., Adang, L., Ovaere, D., Vercruysse, J., 2010. Monitoring the PACS implementation process in a large university hospital-discrepancies between radiologists and physicians. Journal of Digital Imaging, 23 (1), 73–80.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., Williams, M. D., 2019. Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. Information Systems Frontiers, 21 (3), 719–734.

Falk, R. F., Miller, N. B., 1992. A Primer for Soft Modeling. University of Akron Press. Akron, Ohio (USA).

Fan, W., Liu, J., Zhu, S., Pardalos, P. M., 2018. Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS). Annals of Operations Research, 1–26.

Fishbein, M., Ajzen, I., 1975. Belief, attitude, intention, and behavior : an introduction to theory and research. Philosophy & Rhetoric (Vol. 10). Reading, Mass.: Addison-Wesley.

Fuentes-Blasco, M., Moliner-Velázquez, B., Gil-Saura, I., 2017. Exploring relationship variables and Information and Communication Technologies use in industrial segmentation. Management Decision, 55 (7), 1441–1459.

Gabriel, A.M., Goertzel, B., 2019. Distributed, decentralized, and democratized artificial intelligence. Technological Forecasting and Social Change, 141, 354–358.

García, A. S., Fernández-Sotos, P., Fernández-Caballero, A., Navarro, E., Latorre, J. M., Rodriguez-Jimenez, R., González, P., 2019. Acceptance and use of a multi-modal avatar-based tool for remediation of social cognition deficits. Journal of Ambient Intelligence and Humanized Computing, 1–12.

Gartner, 2019. Top 10 Strategic Technology Trends for 2020. Retrieved on April 10, 2020 from https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2020/

Gelbrich, K., Sattler, B., 2014. Anxiety, crowding, and time pressure in public self-service technology acceptance. Journal of Services Marketing, 28 (1), 82–94.

Gharaibeh, M. K., Arshad, M. R. M., 2018. Determinants of intention to use mobile banking in the North of Jordan: extending UTAUT2 with mass media and trust. Journal of Engineering and Applied Sciences, 13 (8), 2023–2033.

Guo, X., Sun, Y., Wang, N., Peng, Z., Yan, Z., 2013. The dark side of elderly acceptance of preventive mobile health services in China. Electronic Markets, 23 (1), 49–61.

Gupta, A., Dogra, N., 2017. Tourist Adoption of Mapping Apps: A UTAUT2 Perspective of Smart Travellers. Tourism and Hospitality Management, 23 (2), 145–161.

Guriting, P., Oly Ndubisi, N., 2006. Borneo online banking: evaluating customer perceptions and behavioural intention. Management Research News, 29 (1/2), 6–15.

Hair, J. F., Sarstedt, M., Ringle, C. M., Mena, J. A., 2012. An assessment of the use of partial least squares structural equation modeling in marketing research. Journal of the Academy of Marketing Science, 40 (3), 414–433.

Heinssen Jr., R. K., Glass, C. R., Knight, L. A., 1987. Assessing computer anxiety: Development and validation of the Computer Anxiety Rating Scale. Computers in Human Behavior, 3 (1), 49–59.

Henseler, J., Ringle, C. M., Sarstedt, M., 2014. A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43 (1), 115–135.

Herrero, Á, San Martín, H., 2017. Explaining the adoption of social networks sites for sharing user-generated content: A revision of the UTAUT2. Computers in Human Behavior, 71, 209–217.

Ho, C. T. B., Chou, Y. T., O'Neill, P., 2010. Technology adoption of mobile learning: A study of podcasting. International Journal of Mobile Communications, 8 (4), 468–485.

Holzmann, P., Schwarz, E. J., Audretsch, D. B., 2018. Understanding the determinants of novel technology adoption among teachers : the case of 3D printing. The Journal of Technology Transfer, 1–17.

Hoy, M. B., 2018. Alexa, Siri, Cortana, and more: an introduction to voice assistants. Medical Reference Services Quarterly, 37 (1), 81–88.

Hsu, C.-L., Lu, H.-P., 2004. Why do people play on-line games? An extended TAM with social influences and flow experience. Information & Management, 41(7), 853–868.

International Finance Corporation, 2020. Artificial intelligence in emerging markets. Retrieved on September 15 from https://www.ifc.org/wps/wcm/connect/95a40480-27b5-4b99-8b4c-7768ae6a53a2/AI-Report_Web.pdf?MOD=AJPERES&CVID=nhLrsRc

Juaneda-Ayensa, E., Mosquera, A., Sierra Murillo, Y., 2016. Omnichannel customer behavior: key drivers of technology acceptance and use and their effects on purchase intention. Frontiers in Psychology, 7, 1–11.

Kaplan, A., Haenlein, M., 2019. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62 (1), 15–25.

Karjaluoto, H., Shaikh, A. A., Saarijärvi, H., Saraniemi, S., 2019. How perceived value drives the use of mobile financial services apps. International Journal of Information Management, 47, 252–261.

Khasawneh, O. Y., 2018. Technophobia without boarders: The influence of technophobia and emotional intelligence on technology acceptance and the moderating influence of organizational climate. Computers in Human Behavior, 88, 210–218.

Kim, D., Park, J., Morrison, A. M., Management, R., Sciences, C., Sciences, F., 2008. A Model of Traveller Acceptance of Mobile Technology, International Journal of Tourism Research, 10 (5), 393–407.

Kim, H. W., Chan, H. C., Gupta, S., 2007. Value-based Adoption of Mobile Internet: An empirical investigation. Decision Support Systems, 43 (1), 111–126.

Kock, N., 2015. Common Method Bias in PLS-SEM: A Full Collinearity Assesment Approach. International Journal of E-Collaboration, 11 (4), 1–10.

Kock, N., Lynn, G. S., 2012. Lateral Collinearity and Misleading Results in Variance-Based SEM : An Illustration and Recommendations. Journal of the Association for Information Systems, 13 (7), 546–580.

Kwon, O., Lee, N., Shin, B., 2014. Data quality management, data usage experience and acquisition intention of big data analytics. International Journal of Information Management, 34 (3), 387–394.

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature, 521(7553), 436–444.

Lee, J.-H., Song, C., 2013. Effects of trust and perceived risk on user acceptance of a new technology service. Social Behavior and Personality: An International Journal, 41 (3), 587–598.

Liao, Y. W., Liu, C. G., Lo, C. L., Su, Z. Y., Wang, C. S., 2018. The Intention to Use the APPs of Smartphone: An Integration of Individual Differences and Browsing Experiences Perspective. Journal of Internet Technology, 19 (2), 439–449.

Limayem, M., Hirt, S. G., Cheung, C. M. K., 2007. How habit limits the predictive power of intention: the case of information systems continuance. MIS Quarterly, 31 (4), 705–737.

Liu, X., 2019. A big data approach to examining social bots on Twitter. Journal of Services Marketing, 33 (4), 369–379.

Liu, J., Chang, H., Forrest, J. Y. L., Yang, B., 2020. Influence of artificial intelligence on technological innovation: Evidence from the panel data of china's manufacturing sectors. Technological Forecasting and Social Change, 158, 1–11.

Luarn, P., Lin, H. H., 2005. Toward an understanding of the behavioral intention to use mobile banking. Computers in Human Behavior, 21 (6), 873–891.

Magsamen-Conrad, K., Upadhyaya, S., Joa, C. Y., Dowd, J., 2015. Bridging the divide: Using UTAUT to predict multigenerational tablet adoption practices. Computers in Human Behavior, 50, 186–196.

Martínez-Córcoles, M., Teichmann, M., Murdvee, M., 2017. Assessing technophobia and technophilia: Development and validation of a questionnaire. Technology in Society, 51, 183–188.

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), 1–13.

Merhi, M., Hone, K., Tarhini, A., 2019. A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTAUT2 with security, privacy and trust. Technology in Society, 59, 1–12.

Moon, J.-W., Kim, Y.-G., 2001. Extending the TAM for a World-Wide-Web context. Information & Management, 38 (4), 217–230.

Moorman, C., Deshpande, R., Zaltman, G., 1993. Factors affecting trust in market research relationships. Journal of Marketing, 57 (1), 81–101.

Morosan, C., DeFranco, A., 2016. It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. International Journal of Hospitality Management, 53, 17–29.

Mosunmola, A., Mayowa, A., Okuboyejo, S., Adeniji, C., 2018. Adoption and use of mobile learning in higher education: the UTAUT model. In Proceedings of the 9th International Conference on E-Education, E-Business, E-Management and E-Learning (pp. 20–25). ACM.

Muhammad, S. S., Dey, B. L., Weerakkody, V., 2018. Analysis of factors that influence customers' willingness to leave big data digital footprints on social media: A systematic review of literature. Information Systems Frontiers, 20 (3), 559–576.

Muñoz-Leiva, F., Climent-Climent, S., Liébana-Cabanillas, F., 2017. Determinants of intention to use the mobile banking apps: An extension of the classic TAM model. Spanish Journal of Marketing-ESIC, 21(1), 25–38.

Niemelä-Nyrhinen, J., 2007. Baby boom consumers and technology: shooting down stereotypes. Journal of Consumer Marketing, 24 (5), 305–312.

Nunnally, J. C., 1978. Psychometric Theory (2nd ed.). McGraw- Hill College.

Nysveen, H., 2005. Intentions to Use Mobile Services: Antecedents and Cross-Service Comparisons. Journal of the Academy of Marketing Science, 33 (3), 330–346.

Oikonomidis, T., Fouskas, K., 2019. A Literature Review of Smartphone Geolocation Technologies. In Strategic Innovative Marketing and Tourism (pp. 1085–1092). Springer.

Oliveira, T., Faria, M., Thomas, M. A., Popovič, A., 2014. Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. International Journal of Information Management, 34 (5), 689–703.

Paavilainen J., Alha K., Korhonen H., 2012. Exploring Playability of Social Network Games. In: Nijholt A., Romão T., Reidsma D. (eds) Advances in Computer Entertainment. ACE 2012. Lecture Notes in Computer Science, vol 7624. Springer, Berlin, Heidelberg

Park, C., 2006. Hedonic and utilitarian values of mobile internet in Korea. International Journal of Mobile Communications, 4 (5), 497–508.

Park, E., Kim, K. J., 2014. An integrated adoption model of mobile cloud services: exploration of key determinants and extension of technology acceptance model. Telematics and Informatics, 31 (3), 376–385.

Park, E., Ohm, J., 2014. Factors influencing users' employment of mobile map services. Telematics and Informatics, 31 (2), 253–265.

Pavlou, P. A., Gefen, D., 2004. Building Effective Online Marketplaces with Institution-Based Trust. Information Systems Research, 15 (1), 37–59.

Peng, M., Zeng, G., Sun, Z., Huang, J., Wang, H., Tian, G., 2018. Personalized app recommendation based on app permissions. World Wide Web, 21 (1), 89–104.

Philip Chen, C. L., Zhang, C. Y., 2014. Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. Information Sciences, 275, 314–347.

Rahman, N., 2016. Factors Affecting Big Data Technology Adoption, 0–29.

Ramírez-Correa, P. E., Rondán-Cataluña, F. J., Arenas-Gaitán, J., 2018. A Posteriori Segmentation of Personal Profiles of Online Video Games' Players. Games and Culture, 1–21.

Ramírez-Correa, P., Rondán-Cataluña, F. J., Arenas-Gaitán, J., Martín-Velicia, F., 2019. Analysing the acceptation of online games in mobile devices: An application of UTAUT2. Journal of Retailing and Consumer Services, 50, 85–93.

Ringle, C. M., Wende, S., Becker, J. M., 2015. SmartPLS. “SmartPLS 3.” Boenningstedt: SmartPLS GmbH.

Roldán, J. L., Sánchez-Franco, M. J., 2012. Variance-Based Structural Equation Modeling: Guidelines for Using Partial Least Squares in Information Systems Research. In M. Mora, O, Gelman, A. L. Steenkamp and M. Raisinghani (coord.) Research Methodologies, Innovations and Philosophies in Software Systems Engineering and Information Systems. IGI-Global (pp.193–221).

Rondan-Cataluña, F. J., Sanchez-Franco, M. J., Villarejo-Ramos, A. F., 2010. Searching for latent class segments in technological services. Service Industries Journal, 30 (6), 831–849.

Shaikh, A. A., Karjaluoto, H., 2015. Mobile banking adoption: A literature review. Telematics and Informatics, 32(1), 129–142.

Shaikh, A. A., Karjaluoto, H., 2016. On some misconceptions concerning digital banking and alternative delivery channels. International Journal of E-Business Research (IJEBR), 12(3), 1–16.

Schepman, A., Rodway, P., 2020. Initial validation of the general attitudes towards Artificial Intelligence Scale. Computers in Human Behavior Reports, 1, 1–13.

Schoorman, F. D., Mayer, R. C., Davis, J. H., 2007. An Integrative Model of Organizational Trust: Past, Present, and Future. Academy of Management Review, 32 (2), 344–354.

Sharif, A., Afshan, S., Qureshi, M. A., 2019. Acceptance of learning management system in university students: an integrating framework of modified UTAUT2 and TTF theories. International Journal of Technology Enhanced Learning, 11 (2), 201–229.

Sharma, V. M., Klein, A., 2020. Consumer perceived value, involvement, trust, susceptibility to interpersonal influence, and intention to participate in online group buying. Journal of Retailing and Consumer Services, 52, 1–11.

Shaw, N., Sergueeva, K., 2019. The non-monetary benefits of mobile commerce: Extending UTAUT2 with perceived value. International Journal of Information Management, 45, 44–55.

Sivarajah, U., Kamal, M. M., Irani, Z., Weerakkody, V., 2016. Critical analysis of Big Data challenges and analytical methods. Journal of Business Research, 70, 263–286.

Solis, B., 2020. How COVID-19 created a new kind of consumer in just 90 days. Retrieved on September 15, 2020 from https://www.fastcompany.com/90547627/how-covid-19-created-a-new-kind-of-consumer-in-just-90-days.

Spain, 2019. Spanish RDI Strategy in Artificial Intelligence. Retrieved on September 15, 2020 from https://www.ciencia.gob.es/stfls/MICINN/Ciencia/Ficheros/Estrategia_Inteligencia_Artificial_EN.PDF (Accessed 10.9.2020)

Statista, 2018. Número de aplicaciones instaladas en los smartphones de los españoles en 2017. Retrieved on August 20, 2020 from https://es.statista.com/estadisticas/724926/apps-instaladas-en-smartphones-espana/

Straub, D., Boudreau, M., Gefen, D., 2004. Validation Guidelines for IS Positivist. Communications of the Association for Information Systems, 13, 380–427.

Sun, T. Q., Medaglia, R., 2019. Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. Government Information Quarterly, 36 (2), 368–383.

Tamilmani, K., Rana, N. P., Dwivedi, Y. K., 2018. Mobile Application Adoption Predictors: Systematic Review of UTAUT2 Studies Using Weight Analysis. In Conference on e-Business, e-Services and e-Society (pp. 1–12). Springer, Cham.

Tamilmani, K., Rana, N. P., Prakasam, N., Dwivedi, Y. K., 2019. The battle of brain vs. heart: a literature review and meta-analysis of "hedonic motivation" use in UTAUT2. International Journal of Information Management, 46, 222–235.

Triguero, I., Peralta, D., Bacardit, J., García, S., Herrera, F., 2015. MRPR: A MapReduce solution for prototype reduction in big data classification. Neurocomputing, 150(Part A), 331–345.

Tussyadiah, I. P., Wang, D., Jung, T. H., Tom Dieck, M. C., 2018. Virtual reality, presence, and attitude change: Empirical evidence from tourism. Tourism Management, 66, 140–154.

Van der Heijden, H., 2004. User acceptance of hedonic information systems. MIS Quarterly, 28 (4), 695–704.

Verdegem, P., De Marez, L., 2011. Rethinking determinants of ICT acceptance: Towards an integrated and comprehensive overview. Technovation, 31(8), 411–423.

Venkatesh, V., 2000. Determinants of perceived ease of use : Integrating control, intrinsic ... Information Systems Research, 11 (4), 342–365.

Venkatesh, V., Morris, M., Davis, G., Fred, D., 2003. User acceptance of information technology : Toward a unified view1. MIS Quarterly, 27 (3), 425–478.

Venkatesh, V., Thong, J. Y. L., Xu, X., 2012. Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quaterly, 36 (1), 157–178.

Verdegem, P., De Marez, L., 2011. Rethinking determinants of ICT acceptance: Towards an integrated and comprehensive overview. Technovation, 31 (8), 411–423.

Waller, M. A., Fawcett, S. E., 2013. Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management. Journal of Busienss Logistics, 34 (2), 77–84.

Wu, I. L., Chen, J. L., 2005. An extension of Trust and TAM model with TPB in the initial adoption of on-line tax: An empirical study. International Journal of Human Computer Studies, 62 (6), 784–808.

Wu, M.-C., Kuo, F.-Y., 2008. An empirical investigation of habitual usage and past usage on technology acceptance evaluations and continuance intention. Database for Advances in Information Systems, 39 (4), 48–73.

Yaqoob, I., Hashem, I. A. T., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N. B., Vasilakos, A. V., 2016. Big data: From beginning to future. International Journal of Information Management, 36 (6), 1231–1247.

Yen, W.-C., Lin, H.-H., Wang, Y.-S., Shih, Y.-W., Cheng, K.-H., 2019. Factors affecting users' continuance intention of mobile social network service. Service Industries Journal, 39 (13–14), 983–1003.

Yu, C.-S., 2012. Factors Affecting Individuals to Adopt Mobile Banking: Empirical Evidence from the UTAUT Model. Journal of Electronic Commerce Research, 13, 104–121.

Zhang, L., Zhu, J., Liu, Q., 2012. A meta-analysis of mobile commerce adoption and the moderating effect of culture. Computers in Human Behavior, 28 (5), 1902–1911.

Zhou, T., 2012. Examining Location-Based Services Usage from the Perspectives of Unified Theory of Acceptance and Use of Technology and Privacy Risk. Journal of Electronic Commerce Research, 13 (2), 135–144.

Zhou, T. (2012). Examining mobile banking user adoption from the perspectives of trust and flow experience. Information Technology and Management, 13(1), 27-37.

Figure 1: Stages of Artificial Intelligence
[Adopted and modified from Kaplan and Haenlein, 2019]

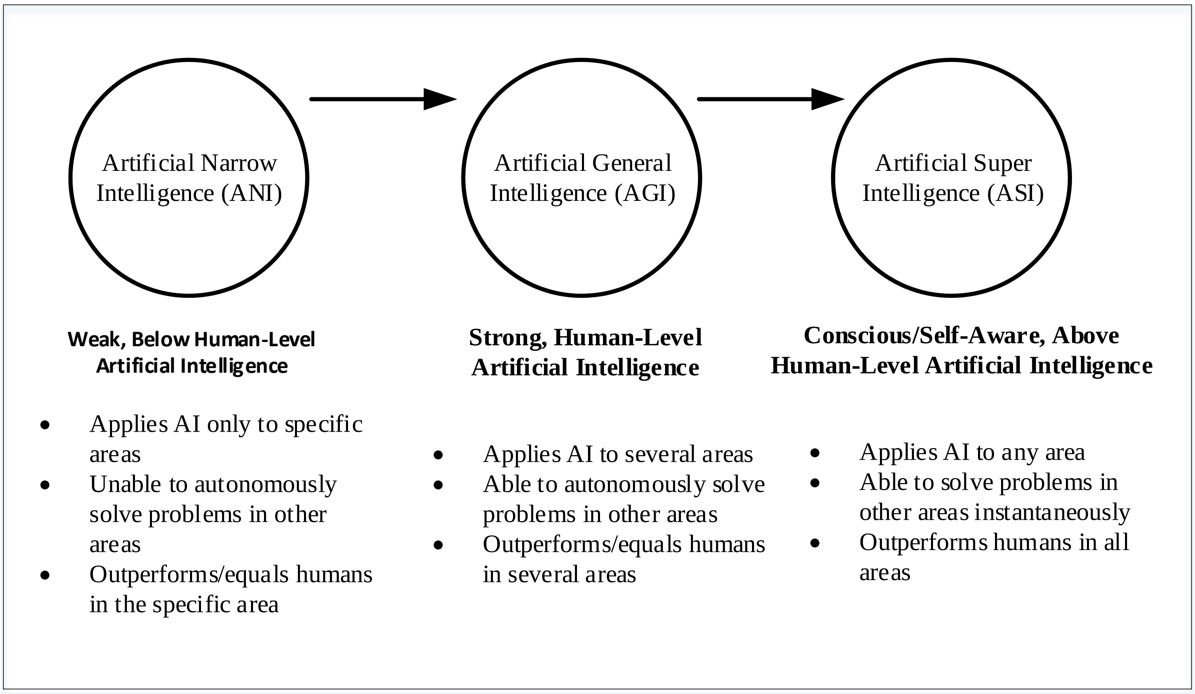

Figure 2: Conceptual Model

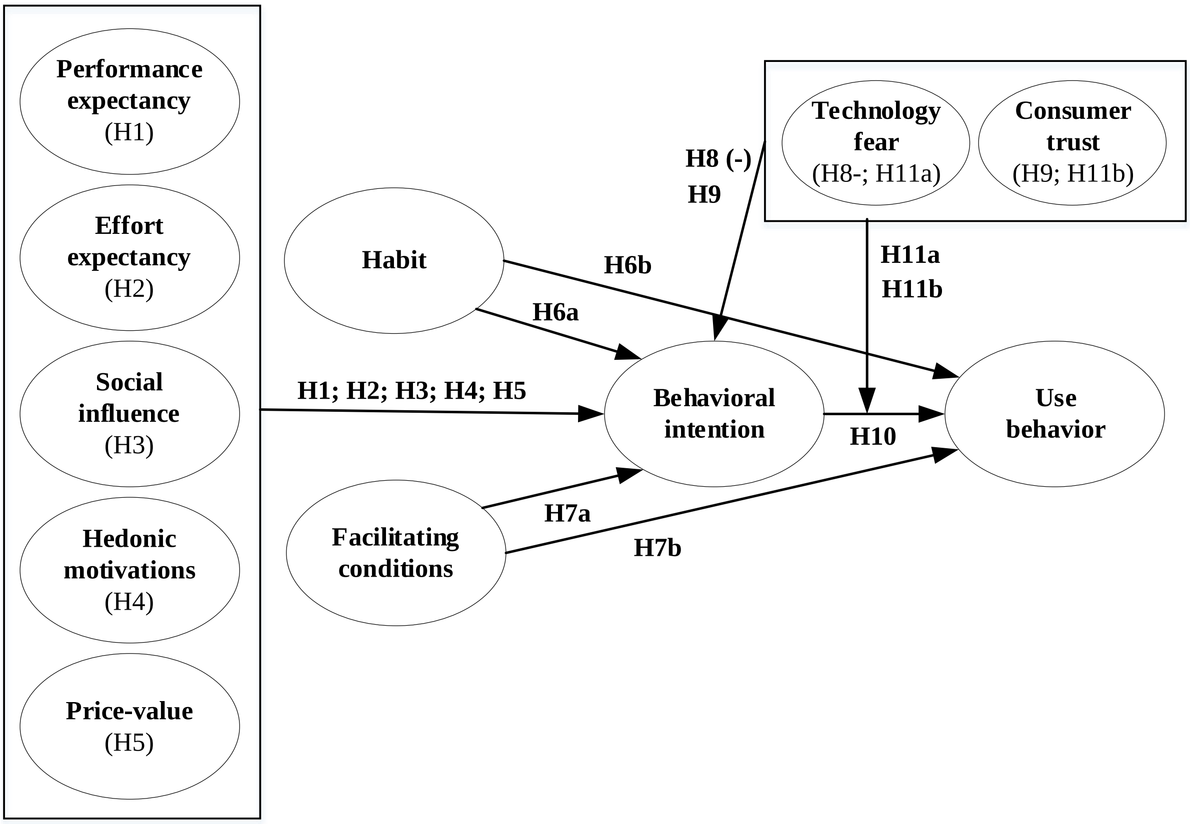

Table 1: VIF from all variables to check CMB

Variables	variable_CMB
Behavioral Intention (BI)	1,940
Effort Expectancy (EE)	1,907
Facilitating Conditions (FC)	1,906
Habit (HT)	1,372
Hedonic Motivation (HM)	1,887
Performance Expectancy (PE)	1,945
Price-value (PV)	1,394
Social Influence (SI)	1,483
Technology Fear (TF)	1,264
Consumer Trust TR)	1,326
Use Behavior UB)	1,254

Table 2: Composite reliability and convergent validity

	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Behavioral Intention	0,899	0,900	0,937	0,832
Effort Expectancy	0,926	0,932	0,948	0,819
Facilitating Conditions	0,809	0,819	0,875	0,638
Habit	0,864	0,873	0,908	0,711
Hedonic Motivation	0,937	0,938	0,960	0,888
Performance Expectancy	0,856	0,858	0,903	0,699
Price-value	0,866	0,887	0,918	0,789
Social Influence	0,935	0,939	0,958	0,885
Technology Fear	0,845	0,963	0,891	0,672
Consumer Trust	0,725	0,744	0,842	0,641
Use Behavior		1,000		

Table 3: Discriminant Validity (Ratio Heterotrait-Monotrait -HTMT)

	BI	EE	FC	HT	HM	PE	PV	SI	TF	TR
BI										
EE	0,436									
FC	0,433	0,734								
HT	0,469	0,366	0,394							
HM	0,604	0,483	0,499	0,417						
PE	0,649	0,390	0,343	0,457	0,607					
PV	0,443	0,328	0,462	0,342	0,442	0,402				
SI	0,441	0,276	0,220	0,346	0,424	0,574	0,324			
TF	0,232	0,410	0,439	0,131	0,207	0,134	0,142	0,062		
TR	0,478	0,263	0,373	0,315	0,423	0,462	0,446	0,326	0,199	

Table 4: R^2 of the model

	R^2	Adjusted R^2
Behavioral Intention	0,473	0,467
Use Behavior	0,182	0,179

Table 5: Structural Model Estimates (*Path Coefficients*)

	Original Sample	**P-values**
H1. Performance Expectancy → Behavioral Intention	0,261***	0,000
H2. Effort Expectancy → Behavioral Intention	0,064 (ns)	0,095
H3. Social Influence → Behavioral Intention	0,081 *	0,020
H4. Hedonic Motivation → Behavioral Intention	0,211 ***	0,000
H5. Price Value → Behavioral Intention	0,085 *	0,021
H6a. Habit → Behavioral Intention	0,118 **	0,001
H6b. Habit → Use Behavior	0,146 ***	0,000
H7a. Facilitating Conditions → Behavioral Intention	0,010 (ns)	0,778
H7b. Facilitating Conditions → Use Behavior	0,090 *	0,023
H8. Technology Fear → Behavioral Intention	-0,084 *	0,010
H9 Consumer Trust → Behavioral Intention	0,110 **	0,002
H10. Behavioural Intention → Usage Beahaviour	0,297 ***	0,000

****p<0.001, **p<0.01, *p<0.05. (It based in 1-tail test and Bootstrap with 10.000 sub-samples).*
(ns) *Non-significant.*

Table 6: Multigroup Analysis with gender

	Path Coefficients -dif. (men - women)	New p-value (men vs women)
Behavioral Intention → Use Behavior	-0,045	0,573
Effort Expectancy → Behavioral Intention	-0,110	0,158
Facilitating Conditions → Behavioral Intention	-0,058	0,449
Facilitating Conditions → Usage Beahaviour	0,236	0,006
Habit → Behavioural Intention	0,087	0,205
Habit → Usage Beahaviour	-0,069	0,413
Hedonic Motivation → Behavioral Intention	-0,044	0,608
Performance Expectancy → Behavioural Intention	0,133	0,111
Price Value → Behavioural Intention	-0,034	0,637
Social Influence → Behavioral Intention	0,023	0,743
Technology Fear → Behavioral Intention	-0,100	0,101
Consumer Trust → Behavioral Intention	-0,019	0,796

Table 7: Multigroup Analysis with Income

	Path Coefficients - dif. (<1800€- <1800€)	New p-value (<1800€ vs <1800€)
Behavioral Intention → Use Behavior	-0,011	0,900
Effort Expectancy → Behavioral Intention	0,004	0,955
Facilitating Conditions → Behavioral Intention	0,092	0,252
Facilitating Conditions → Use Behavior	-0,151	0,122
Habit → Behavioral Intention	0,000	0,991
Habit → Usage Behavior	-0,028	0,765
Hedonic Motivation → Behavioral Intention	-0,229	0,008
Performance Expectancy → Behavioral Intention	0,088	0,294
Price-value → Behavioral Intention	-0,080	0,274
Social Influence → Behavioral Intention	0,113	0,125
Technology Fear → Behavioral Intention	-0,046	0,483
Consumer Trust → Behavioral Intention	0,017	0,819

Table 8: Indirect effects of TF and Trust in Usage

		Path	P-Values
H11a	Technology Fear → Behavioral Intention → Use Behavior	-0,025 *	0,010
H11b	Consumer Trust → Behavioral Intention → Use Behavior	0,033 **	0,002

***p<0.001, **p<0.01, *p<0.05. (It based in 1-tail test and Bootstrap with 10.000 sub-samples).

Table 9: Average R^2

R squared (by number of segments)	**Original sample** (without segments)	**2 segments**	**3 segments**	**4 segments**	**5 segments**	**6 or more**
Behavioural Intention	0.454	0.483	0.493	Error	0.735	Error
Usage Behaviour	0.178	0.195	0.275	Error	0.602	Error
Average R^2	0.316	0.339	0.384	Error	0.669	Error

Table 10: Path coefficients and p-values (original model vs segmented model)

	Original	Seg 1 (28)		Seg 2 (211)		Seg 3 (156)		Seg 4 (263)		Seg 5 (82)	
PE → BI	**0.286**	**-0.849**	0.002	**0.404**	0.000	**0.450**	0.000	**0.274**	0.000	**-0.120**	0.044
EE → BI	**0.084**	**0.383**	0.011	**-0.212**	0.000	**-0.134**	0.031	**0.532**	0.000	0.014	0.417
SI → BI	**0.088**	0.006	0.490	**-0.171**	0.000	**0.163**	0.009	**0.257**	0.000	**0.341**	0.000
HM → BI	**0.230**	**0.753**	0.000	**0.431**	0.000	**-0.106**	0.007	**0.084**	0.037	**0.950**	0.000
PV → BI	**0.107**	-0.147	0.185	0.062	0.073	**0.554**	0.000	**-0.241**	0.000	0.056	0.130
HT → BI	**0.092**	**0.604**	0.000	-0.044	0.165	0.053	0.205	**0.184**	0.000	-0.061	0.156
HT → UB	**0.098**	**0.537**	0.000	**-0.145**	0.001	**0.468**	0.000	-0.058	0.131	**0.192**	0.000
FC → BI	0.055	0.262	0.063	**0.433**	0.000	**-0.189**	0.002	-0.043	0.225	**-0.319**	0.002
FC → UB	**0.103**	**0.106**	0.047	**-0.777**	0.000	**0.427**	0.000	**0.758**	0.000	**-0.233**	0.001

Bold: significant path.

Table 11: R^2 of endogenous variables

	R squared original sample	POS-Seg 1	POS-Seg 2	POS-Seg 3	POS-Seg 4	POS-Seg 5
Behavioral Intention	0.454	0.979	0.719	0.715	0.694	0.861
Use Behavior	0.178	0.979	0.632	0.673	0.408	0.880

Table 12: ANOVA and p-values of every variable and segment

Significant differences between segments					Not significant differences between segments				
Variable	*Segment*	*N*	*Mean*	*Significance*	*Variable*	*Segment*	*N*	*Mean*	*Significance*
Behavioral Intention	1	28	-0.0412	**0.009**	Facilitating Conditions	1	28	0.1708	0.076
	2	211	0.0949			2	211	0.0597	
	3	156	-0.2402			3	156	-0.0727	
	4	263	0.0914			4	263	0.0560	
	5	82	-0.0661			5	82	-0.2528	
	Total	740	0.0000			Total	740	0.0000	
Effort Expectancy	1	28	0.0247	**0.010**	Habit	1	28	-0.0427	0.102
	2	211	0.0618			2	211	-0.0008	
	3	156	-0.1828			3	156	-0.1793	
	4	263	0.1203			4	263	0.0726	
	5	82	-0.2053			5	82	0.1244	
	Total	740	0.0000			Total	740	-0.0001	
Hedonic Motivation	1	28	0.3299	**0.013**	Performance Expectancy	1	28	-0.0363	0.145
	2	211	0.1007			2	211	0.0637	
	3	156	-0.1813			3	156	-0.1258	
	4	263	0.0400			4	263	0.0757	
	5	82	-0.1554			5	82	-0.1548	
	Total	740	0.0000			Total	740	0.0000	
Price-value	1	28	0.0429	**0.029**	Social Influence	1	28	0.2306	0.178
	2	211	-0.0249			2	211	-0.0258	
	3	156	-0.1200			3	156	-0.1189	
	4	263	0.1444			4	263	0.0887	
	5	82	-0.1859			5	82	-0.0700	
	Total	740	-0.0001			Total	740	0.0000	
Technology Fear	1	28	-0.3162	**0.027**	Usage Behaviour	1	28	-0.1058	0.201
	2	211	-0.0811			2	211	0.0232	
	3	156	0.2002			3	156	-0.1553	
	4	263	-0.0357			4	263	0.0468	
	5	82	0.0501			5	82	0.1220	

	Total	740	0.0000			Total	740	0.0000	
Consumer Trust	1	28	0.1068	**0.041**					
	2	211	0.0099						
	3	156	-0.1281						
	4	263	0.1195						
	5	82	-0.2013						
	Total	740	0.0000						

Table 13: Segments obtained in the POS-PLS latent class segmentation

N	28	211	156	263	82
	Segment 1	**Segment 2**	**Segment 3**	**Segment 4**	**Segment 5**
BI	-0.0412	**0.0949**	-0.2402	**0.0914**	-0.0661
EE	0.0247	0.0618	-0.1828	0.1203	**-0.2053**
HM	**0.3299**	**0.1007**	-0.1813	0.0400	-0.1554
PV	0.0429	-0.0249	-0.1200	**0.1444**	-0.1859
TF	**-0.3162**	-0.0811	**0.2002**	-0.0357	0.0501
TR	**0.1068**	0.0099	**-0.1281**	**0.1195**	-0.2013

ANNEX I: Measurement Scales

Effort expectancy	EE1: I find it easy to learn to use AI tools. EE2: My interaction with AI tools is clear. EE3: I find it easy to use AI. EE4: I believe that learning to use an AI application is easy for me.
Performance expectancy	PE1: I believe that AI is useful for me in my day-to-day life. PE2: I believe that AI will help me achieve things that are important to me. PE3: I believe that AI helps me carry out my tasks quickly. PE4: I believe that AI improves my performance.
Social influence	SI1: People who I care about think I should use AI applications. SI2: People who influence my behavior think that I should use AI. SI3: People whose opinion I value believe that I should use AI apps.
Hedonic motivations	HM1: Using AI applications is fun. HM2: I enjoy using AI applications. HM3: Using AI applications is very entertaining.
Price value	PV1: AI applications are reasonably priced. PV2: AI applications are worth what they cost. PV3: At the current price, AI gives good value.
Habit	HT1: The use of AI has become a habit for me. HT2: I am an AI addict. HT3: I must use AI applications. HT4: Using AI has become something natural for me.
Facilitating condition	FC1: I have the necessary resources to use AI. FC2: I have the necessary knowledge to use AI applications. FC3: AI is compatible with other applications that I use. FC4: When I have trouble using AI applications, I can get help.
Behavioral intention	BI1: I intend to use AI applications soon. BI2: I will always try to use AI applications in my daily life. BI3: I plan to use AI applications frequently.
Use behavior	UB1 Maps: What is your current use of the maps and routes? UB2 Recommendations: What is your current use of the recommendations? UB3 Voice: What is your current use of voice recognition?
Technology fear	TF1: I hesitate to use Artificial Intelligence because I am afraid of making mistakes that I cannot correct. TF2: I dislike working with machines that are smarter than me. TF3: I am afraid of working with Artificial Intelligence. TF4: I fear being dependent on Artificial Intelligence and losing some of my skills. TF5: I feel distressed when working with Artificial Intelligence. TF6: I feel unsure of my ability to understand Artificial Intelligence. TF7: I have avoided Artificial Intelligence because it is unfamiliar and, in a way, intimidating to me.
Consumer trust	TR1: Artificial Intelligence can be trusted. TR2: Artificial Intelligence does what it promises. TR3: Artificial Intelligence is concerned with satisfying the user.