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Biometric m-payment systems: A multi-analytical approach to determining use intention

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ABSTRACT

Although mobile payment systems offer countless advantages, they do present certain drawbacks, mainly associated with security and privacy concerns. The inclusion of biometric authentication technologies seeks to minimise such drawbacks. The aim of this article is to examine the effect of key antecedents of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and perceived risk on the intention to use a mobile payment system featuring biometric identification. A new hybrid analytical approach is taken. A sample of more than 2500 smartphone users was obtained through an online panel-based survey. Two techniques were used: first, structural equation modelling (PLS-SEM) was conducted to determine which variables had a significant influence on the adoption of the mobile payment system, and second, an artificial neural network (ANN) model was used, taking a deep learning approach, to rank the relative influence of significant predictors of use intention obtained via PLS-SEM. The study found that the most significant variables affecting use intention were performance expectancy, effort expectancy, facilitating conditions, hedonic motivation and risk. In contrast, subjective norms, price value and habit were found to be weak predictors of use intention. The results of the ANN analysis confirmed almost all SEM findings but yielded a slightly different order of influence among the least significant predictors. A review of the extant scientific literature revealed a paucity of published studies dealing with the adoption and use of mobile payment systems featuring biometric identification. The conclusions and managerial implications point to new business opportunities that can be exploited by firms through the use of this technology.

1. Introduction

1.1. The emergence of biometric payment systems: market trends

As society evolves, the payment systems used by citizens also change. User behaviour has shifted rapidly in recent years, moving away from more traditional payment systems, such as cash and bank cards, in favour of alternatives such as payment via mobile devices (m-payment) using Near Field Communication (NFC) or Quick Response (QR) codes [1]. A recent report by PwC [2] predicts that, compared to 2020, global cashless payment volumes will increase by more than 80 % by 2025, from about 1tn transactions to almost 1.9tn, and will have almost tripled by 2030. The PwC study identifies the Asia-Pacific region as the fastest growing of all, with cashless transaction volumes there expected to witness growth of 109 % by 2025, followed by Africa (78 %) and Europe (64 %). In the Euro area alone, the total number of cashless payments, which comprises all types of payment services, increased by 3.7 % to 101.6bn in 2020 compared with the previous year, and the total value increased by 8.7 % to €167.3tn [3]. Card payments accounted for 47 % of all transactions, whereas credit transfers accounted for 23 % and direct debits 22 % (ibid.). Moreover, according to Ditrendia, more than 111 billion cashless transactions were made in Europe in 2019, led by the UK (27 billion), France (23 billion), Germany (22 billion), and the Netherlands and Spain (8 billion each) [4]. Finally, worldwide, the volume of m-payment transactions at the point of sale reached €901bn in 2020. All these payment systems offer countless advantages but also certain drawbacks, mainly associated with security and privacy concerns [5]. Thus, in view of their benefits, it is essential to explore the reasons behind such a slow transition from cash to m-payment [6].

It is against this backdrop that *biometric* payment systems have

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emerged in recent years in a bid to minimise the drawbacks that plague other payment systems—albeit this is not always appreciated by users [7]. Biometrics is a technique that enables individuals' identities to be authenticated by means of (1) a physical trait (e.g., fingerprints, palm prints, and face- or iris recognition), which are generally inherent and stable, or (2) a behavioural trait (e.g., voice, signature or keystroke dynamics), which are generally quantifiable characteristics [8]. This technique is now available globally to protect and verify the personal identity of users. However, even though the use of biometric authentication is *possible* [9,10] and such technologies are available on the market, they are not yet widely implemented, as various factors impede their effectiveness.

There are several types of biometric authentication that can be used to support the privacy and security of end users without the need to have their entire identity stored in the cloud. Sulaiman and Almunawar [11] proposed three main approaches to biometric template protection that can be distinguished: (1) biometric cryptosystems or secure sketches, which use cryptography; (2) secure computing methods designed to compare two biometric templates from an untrusted party; and (3) a BioHashing algorithm, which is based on biometric data salting and one of the most popular techniques.

A biometric system is a pattern recognition system that acquires biometric data from an individual, extracts a set of features from that data and compares those features with the template set in the database [12]. Several human traits are compatible with this definition of biometrics [9]. To be used to recognise a person, the trait must be unique and not subject to change, although no biometric information can guarantee 100 % accuracy. Among the biometric data in common use are DNA (deoxyribonucleic acid), ear and face recognition, fingerprints, gait, hand and finger geometry, iris and retina scanning, signature verification, and voice recognition.

Regarding the use of biometrics in payment systems, leading providers such as MasterCard are already developing specific applications to employ these techniques for payment purposes. For example, the use of voice recognition in ATMs or vending machines enables firms to validate payments that customers have authorised using fingerprint recognition, which also frees consumers from the need to remember codes or passwords. Facial recognition is also used as a part of certain sales transactions. The primary benefits of this technology are associated with security and the reliable identification of users [13].

With 15.9 billion mobile devices in operation across the world in 2022, and with this figure projected to reach 18.2 billion by 2025 [14], the potential of mobile biometrics is evident, as it provides a more convenient and secure way to access mobile apps and services than traditional passwords or personal identification numbers (PINs). In 2018, more than 60 % of smartphones came equipped with fingerprint sensors, and in 2020, 64 % of smartphones worldwide used facial recognition technology [15]. The global mobile biometrics market was valued at $24.6bn in 2021 [16] and is set to reach US$91.9bn by 2028 [17]. This figure is projected to grow to US$208bn by 2032, representing a compound annual growth rate of 21.2 % from 2022 [18].

As of 2021, the mobile biometric market was dominated by North America [16], where it enjoyed an estimated market size of US$12.2bn in 2022 [14]. It is expected to retain its position in the next decade, mainly because of a high concentration of mobile biometric solution vendors in the region and the growing adoption of mobile payments. Another key region is Asia-Pacific, with a share of 35 % of the mobile biometrics market [19], primarily thanks to the presence of highly populated countries such as India, China and Japan, and high mobile payment acceptance rates in the latter two.

The recent COVID-19 pandemic had a positive impact on the mobile biometrics market [16,17] due to a significant rise in e-commerce, which, in turn, prompted an increase in the use of digital payments. Industry-wise, BFSI (banking, financial services and insurance) is forecast to remain the leading user of mobile biometrics [14]. By using biometric authentication, banks can minimise the risk of fraud and unauthorised access, and can make transactions faster and more convenient for customers.

Currently, fingerprint recognition is the most commonly used biometric technology globally [17], followed by face recognition and voice recognition. Fingerprint recognition is expected to remain the first choice in the next decade [18], because even low-cost mobile devices, affordable to most consumers worldwide, now typically come with a fingerprint biometrics option.

1.2. Application of biometrics in mobile devices

As Apple's iOS and Google's Android are the leading mobile operating systems, covering more than 99.3 % of the market [20], it is interesting to compare the adoption of biometrics by mobile devices using these two platforms. For example, Wetherill [21] states that biometric authentication is one of the most important strategic differentiators between iOS and Android devices. The introduction of a face recognition system on Android 4.0 (2011) and a Touch ID fingerprint recognition system on the iPhone 5S (2013) brought biometric authentication to more users than ever before [22].

Apple's iOS is available on devices such as iPhones and iPads, and is well known for its excellent user experience but also for its strong emphasis on security and privacy [23]. One of the most important features of Apple devices is their use of hardware-based encryption to protect user data, which makes it hard for hackers to access and steal sensitive user information. Two of Apple's main biometric authentication features, Touch ID for fingerprint recognition and Face ID for facial recognition, also use hardware-based encryption to protect users' biometric data, which provides an additional layer of security [23]. Recently, Apple applied for a patent to capture face, fingerprint and iris biometrics from under the device's display [24], and it is expected that devices with this feature will be ready for the market by 2025. Apple has also added a further layer of multifactor authentication security for iPhones, in the form of security keys—physical objects, such as NFC tokens or USB devices [25]. This means that to unlock the phone, in addition to face or fingerprint recognition, the security key must either be in close proximity to the device or plugged directly into it.

Meanwhile, Google's Android is an open-source operating system available on various mobile devices and produced by various manufacturers [23]. Its open-source nature allows Android to gain a significant market share (particularly at the lower end of the market), with many different devices, but each manufacturer may have its own approach to security. For example, some manufacturers and Android devices offer retinal and fingerprint scanners, but a few of them are limited only to passwords and patterns as protection measures [26]. Samsung's Galaxy Note 7 was one of the first Android devices with facial recognition based on iris scanning [21]. Samsung devices have started to offer four different forms of biometric authentication: facial recognition, iris scanning, fingerprint recognition, and a combination of facial and iris scanning. Despite such advancements, however, because iOS device security features are more restrictive and well integrated than those of Androids, Apple devices are considered more secure [26,27].

In the ongoing quest to maximise mobile device security, recent estimates [23] predict the increased use of biometric authentication beyond the already widespread fingerprint and face recognition, to include voice recognition, iris scanning and brainwave analysis. However, even though biometric authentication is generally more secure than a four-digit PIN or passcode, it is not infallible—there are numerous examples of facial recognition systems being duped by user photographs or family members with similar features [21].

1.3. Objectives of the study

The present review of the scientific literature finds a paucity of studies dealing with the adoption and use of biometrics applied to payment systems. To address this research gap, the study pursues the following objectives:

(1) To contribute to deepening the understanding of consumer behaviour relating to biometric m-payment systems (BMPS) and identify the determinants and barriers affecting their adoption
(2) To develop a conceptual framework to better understand the antecedents and consequences of the intention to use BMPS based on a modified version of the Unified Theory of Acceptance and Use of Technology (UTAUT2), including the principles of Perceived Risk Theory (PRT).

By taking this hybrid approach, the results of this study will contribute to the existing knowledge regarding m-payment systems, providing a new perspective from SEM and ANN modelling for assessing and understanding the driving factors in users' adoption of BMPS. This approach will also enable the types of relationships between the predictors and the endogenous variable to be evaluated.

We now turn to the theoretical background (Section 2), followed by the development of the conceptual model and hypotheses (Sections 3 and 4) and the research methodology (Section 5). The discussion, together with conclusions, the implications of the findings, limitations and future research directions, is presented in Section 6.

2. Biometric payment systems

The growth of the internet as a global mass communication medium has rendered digital monetary transactions—including contactless systems—possible. However, the fluidity of contactless payment and the sheer diversity of systems available constitute something of a barrier for consumers, due to the trust issues and risk concerns surrounding biometric payments [28].

Recent technological developments have meant that traditional payment systems (cash or bank cards) are starting to decline in prominence and are being replaced by new contactless payment systems using new media (contactless cards or mobile devices) [29]. Biometric payments therefore offer opportunities for both users and merchants. Biometric technology can be defined as a form of personal identification, based on psychological or behavioural characteristics, to reduce transaction risk and improve trust among shoppers [30,31]. Providing a sense of the potential worldwide scale of these burgeoning systems, a study by Juniper Research [32] shows that approximately 1.4 billion people will use biometrics for payments by 2025. According to Juniper, "the value of biometrically authenticated remote mobile payments will reach $1.2 trillion globally by 2027; rising from $332 billion in 2022″.

To overcome the limitations of conventional payment methods, advanced authentication schemes have been developed to provide consumers with improved security [33]. In particular, biometric technology based on personal uniqueness (i.e., physical traits) is being successfully deployed to provide secure user authentication [34]. Although there are multiple biometric systems that can identify users, the leading payment systems using biometrics tend to favour four techniques in particular: fingerprint recognition, finger vein recognition, facial recognition and iris scanning [35]. The literature has examined these payment systems primarily from a technical perspective, paying scant attention to behavioural aspects [36].

Some major banks already use biometric technologies in different scenarios, such as cash withdrawals at the ATM, mobile-banking apps using fingerprint recognition for authentication, or a combination of face and voice verification [37]. For instance, in 2015, Bank of America implemented fingerprint authentication and Touch ID, and by mid-2017, more than half of its customers were using biometrics for mobile app access. In the UK, Tesco Bank made its mobile banking app compatible with Apple's Face ID, which has enabled customers to access their accounts and make payments by using facial recognition [37].

Juniper Research [38] predicts that facial recognition will be used by more than 1.4 billion customers for payment authentication by 2025, and a global market survey by Dentsu Data Lab and Idemia found that 81 % of consumers are prepared to use fingerprint recognition instead of a PIN to authenticate payments [39]. A survey conducted by Visa in 2022 revealed that 86 % of consumers are interested in using biometrics to authenticate their identity for making payments [40]. The majority, 70 %, agree that biometrics are easier to use, whereas 46 % believe that biometric systems are more secure than passwords or PINs.

In addition, the new European Union Payment Services Directive (PSD2) regulating electronic payments (e.g., virtual POS, e-wallets or e-banking) requires businesses and financial institutions to use at least one of the following three authentication systems: (1) something known only to the user (password or security PIN), (2) something held by the customer (validation by inputting a code sent to their mobile phone), and (3) something inherent to the user themselves (iris or fingerprint). This new regulation will exclude payments made only with card details.

The implementation of biometric solutions in the authentication processes set out under the PSD2 regulation has significantly increased, largely due to their ability to streamline consumer verification and because they are now familiar to many users. In fact, since the introduction of biometrics on mobile devices, such as fingerprint or facial recognition for unlocking, most users are familiar with these practices. Furthermore, on 21 June 2019, the European Banking Authority expressed support for implementing biometric methods within identity verification processes under the PSD2 regulation.

Given this general context, strikingly little research has been conducted into consumer acceptance of BMPS; hence, the present study makes a relevant contribution to addressing that gap.

3. Theoretical background and research model

3.1. UTAUT2

Many researchers have conducted studies on the adoption and use of information technologies or systems [41]. These studies have employed classical theories, such as the Theory of Reasoned Action (TRA) [42], based on the constructs of subjective norms, attitude, intention and use; the Theory of Planned Behaviour (TPB) [43], based on subjective norms, perceived control, attitude, intention and use; or the Technology Acceptance Model (TAM) [44], based on ease of use, usefulness, attitude, intention and use. With regard to adaptations to the TAM, Venkatesh and Davis [45] developed TAM2 by extending the original model to further explain usefulness, based on four characteristic factors of the system and cognitive processes that focus on the characteristics of information technology and its potential to positively impact on work processes and outcomes. The latest adaptation to the TAM is TAM3 [46], which includes two new sets of determinants of the ease-of-use construct.

As a result of adaptations to the original TAM, Venkatesh et al. [47] designed the Unified Theory of Acceptance and Use of Technology (UTAUT), which includes determinants such as performance expectancy, effort expectancy, social influence and other conditions that facilitate acceptance. The UTAUT model was subsequently extended to the consumer context, emphasising the hedonic values (intrinsic motivation) of technology users and incorporating three new constructs—hedonic motivation, price value and habit—with the extended model being popularly referred to as UTAUT2 [48]. In particular, the UTAUT2 (including its later extensions) has recently been defined as one of the most widely used models in the scientific literature for analysing the process of innovation adoption [49]. We therefore selected this model to analyse the adoption of BMPS. In line with Singh et al. [50] and Migliore et al. [51], we find UTAUT2 to be better suited to our research than other technology acceptance models, as it facilitates a better understanding of the main determinant constructs for explaining behavioural intention.

Some researchers have specifically used these methodological proposals in the context of m-payment services. Gupta and Arora [52] confirmed that performance expectancy, effort expectancy, habit and facilitating conditions significantly predicted behavioural intention, which, in turn, significantly predicted m-payment system usage behaviour; in contrast, both social influence and hedonic motivation were weak predictors of behavioural intention. Morosan and DeFranco [53] found that performance expectancy was the highest predictor of intentions, whereas hedonic motivations, habit and social influences all had a relatively weak effect. Widyanto et al. [54] found that social influence, hedonic motivation, and trust directly and significantly affected behavioural intention, whereas effort expectancy, perceived security and performance expectancy had an indirect relationship with behavioural intention. The present research model extends the UTAUT2 by adding perceived risk, as this is considered one of the most important variables in the analysis of m-payment adoption ([55]; Liébana-Cabanillas et al., 2021).

3.1.1. Performance expectancy

Performance expectancy refers to the extent to which an individual believes that using a certain technology will improve their performance [47]. In our case, performance expectancy will improve use intention towards the BMPS analysed in the research. This relationship has been tested in numerous research studies. Typically, users of BMPS will have a greater use for the benefits and advantages that these systems offer, leading to greater use intention [56,57]. The following hypothesis is therefore proposed:

H1: Performance expectancy has a positive effect on the intention to use BMPS.

3.1.2. Effort expectancy

Effort expectancy is defined as the degree of ease associated with using a given technology [48]. Depending on whether the individual considers biometric m-payment to be easy or difficult to manage, they will be more or less inclined to use it.

Studies claim that the use of biometric systems offers specific benefits, including effort savings and time convenience [58]. Regarding effort, in particular, Ogbanufe and Kim [59] concluded that perceived usage effort should be measured to increase understanding of biometric payment systems, since effort expectancy is a driver of the use of biometrics during payment and checkout. This approach has been supported by numerous studies dealing with m-payment, where the relationship between effort expectancy and behavioural intention is confirmed [60,61]. Hence, the following hypothesis is proposed:

H2: Effort expectancy has a positive effect on the behavioural intention to use BMPS.

3.1.3. Subjective norms

Fishbein and Ajzen [42] defined subjective norms as the degree to which individuals perceive that people whose opinions matter to them think they should (or should not) use a given system or perform a certain action or behaviour. In the present context, regarding the acceptance of a new payment system using biometrics, users might feel unsure about the consequences of using it and, thus, may draw on the opinions and experiences of their most trusted contacts before forming any use intention [62,63]. They may also rely on the feedback, opinions and experiences of other users to improve their final use intention [64]. The following hypothesis is therefore proposed:

H3: Subjective norms have a positive effect on the intention to use BMPS.

3.1.4. Facilitating conditions

Facilitating conditions—another variable proposed in UTAUT2—are the factors that act as facilitators or barriers in the environment that influence a person's perception of the ease or difficulty of performing a task. In our case, BMPS offer a new service not yet widely implemented in society, so using them will require individuals to possess certain skills, such as configuring the mobile phone correctly. To the extent that users have these skills, their end use intention will improve; otherwise, they will not use this new payment system. Other authors have found facilitating conditions to be a significant predictor of behavioural intention [57,65]. Thus, the following hypothesis is proposed:

H4: Facilitating conditions have a positive effect on the intention to use BMPS.

3.1.5. Hedonic motivation

Along with extrinsic motivations (performance expectancy and effort expectancy), intrinsic motivation is considered another important driver of intention for users to access new technologies and applications [66]. The main purpose of using hedonic motivation in the present research is to capture the emotional feeling and response of individuals as a result of adopting BMPS. According to Venkatesh et al. [48], hedonic motivation is defined as the fun or pleasure that using a particular technology stimulates in the individual. In this research, it refers to the enjoyment and pleasure derived from adopting BMPS. The rationale behind hedonic motivation is that if the use of a technology enhances pleasurable experiences and feelings, individuals will be willing to accept and use it because of the natural tendency to take actions towards achieving useful and positive experiences.

For the context of the present study, hedonic motivation is taken to reflect users' feelings towards BMPS as an attractive and enjoyable technology for their secure payment experience and purposes. Numerous studies have demonstrated the ability of payment systems to add fun aspects to the interactive experience (Morosan et al., 2016; [67]). Accordingly, the following research hypothesis is proposed:

H5: Hedonic motivation has a positive effect on the intention to use BMPS.

3.1.6. Price value

Venkatesh et al. [48] defined price value as consumers' cognitive trade-offs between the perceived benefits of apps and the cost of using them. Tamilmani et al. [68] subsequently conducted an important literature review to verify the importance of this variable in the UTAUT2 model, confirming its relationship as one of the main antecedents of intention and use. This relationship has been found in numerous contexts [69] and specifically in relation to payments [70]. In the present study, consumers who positively value the use of BMPS in relation to the cost of adoption will present improved use intention towards m-payment. Thus, the following hypothesis is proposed:

H6: Price value has a positive effect on the intention to use BMPS.

3.1.7. Habit

In various studies, habit has been found to be a predictor of technology use [71]. Escobar-Rodríguez et al. [72] reviewed different definitions by several authors who related it to previous behaviour, automatic behaviour or even automaticity. In our case, we take 'habit' to be the extent to which users automatically perform certain behaviours due to the learning they have acquired; it therefore increases their use intention towards BMPS. Several articles have contributed to the literature on habit in payment platforms [69,73]. In this study, we will assume that users who are already in the habit of using payment systems other than traditional ones will present greater use intention towards BMPS. On this basis, the following hypothesis is proposed:

H7: Habit has a positive effect on the intention to use BMPS.

3.2. Perceived risk theory

To complete the modification of the UTAUT2 model, the inclusion of perceived risk from PRT is proposed here. This theory is based on the principles of Bauer (1960), who stated that consumers' purchasing behaviours carry a certain risk because purchasing decisions can have unpredictable or unfavourable consequences. This author proposes that risk has two components: uncertainty (the consumer's lack of knowledge of what may happen when making the purchase) and the possible negative consequences of the purchase. This theory has been used in studies dealing with m-payment [74], although not always with the expected results [75].

Perceived risk has been defined by several authors. According to Cunningham and Gerrard [76], perceived risk is the possibility that the use of the innovation is not certain, whereas Gupta and Kim [77] defined it as a consumer's perception of the uncertainty and possible adverse consequences of entering into a transaction with the seller.

Despite numerous studies having analysed this variable, it presents a high degree of complexity because it is considered a multidimensional construct involving different factors that jointly explain the overall risk associated with the adoption of, purchase of or payment for a service [5]. The dimensions of risk were originally identified as performance risk, financial risk, psychological risk and social risk [78], with two further dimensions subsequently added: physical risk and temporal risk. The present study analyses the perceived risk of using BMPS in *overall* terms, following the approach taken by Liébana-Cabanillas et al. (2021), among others.

The proposed extension of the UTAUT2 model refers to perceived risk, which is defined as consumers' perception of the potential for loss in the pursuit of the desired outcome when using a given payment system (biometric m-payment, in this case) [79]. As perceived risk reflects consumers' perceptions of uncertainty about the outcome of a transaction [80], it may restrict their use intention. In numerous studies on the topic of payment system adoption, perceived risk is considered a critical factor that negatively affects adoption [57,81,82]. In this study, we analyse the perception of risk among potential users of BMPS. The following hypothesis is therefore proposed:

H8: Perceived risk has a negative effect on the intention to use BMPS.

Fig. 1 shows the proposed conceptual model for the research hypotheses.

4. Research methodology

4.1. Measurements

The questionnaire primarily consisted of a series of statements that respondents were asked to rate along a 7-point Likert scale on which 1="strongly disagree" and 7="strongly agree". This enabled us to analyse the factors indicated by the prior literature review. The measurement scales were adapted from previous studies. Given that we were working with a translated version of the questionnaire (in Spanish), we had the final version translated back into English by a professional native English translator to ensure consistency between the versions [83]. Table 3 details the measurement scales used as well as the original studies from which they were adapted.

4.2. Sample and data collection

Data collection was carried out via a self-administered online survey between November 2020 and January 2021. After data cleaning, the final sample comprised 2586 individuals. We used convenience sampling (nonprobability), distributing a link to the survey via social networks and email lists.

First, an initial review (first phase) of both the methodology to be used and the scales extracted from the scientific literature was carried out by a panel of 10 experts. This review, which was performed on the basis of personal interviews, led us to modify some of the proposed scales and adapt some others to the main objective. Following this review by the expert panel, we divided the questionnaire into three thematic blocks: control questions, questions on the object of the research and sociodemographic data, with a total of 20 items.

After this first phase, we selected the payment system to be analysed. We opted for the PayEye payment system (https://payeye.com/en/) due to its level of innovation compared to other alternatives. To ensure that participants were aware of it and would answer the questionnaire

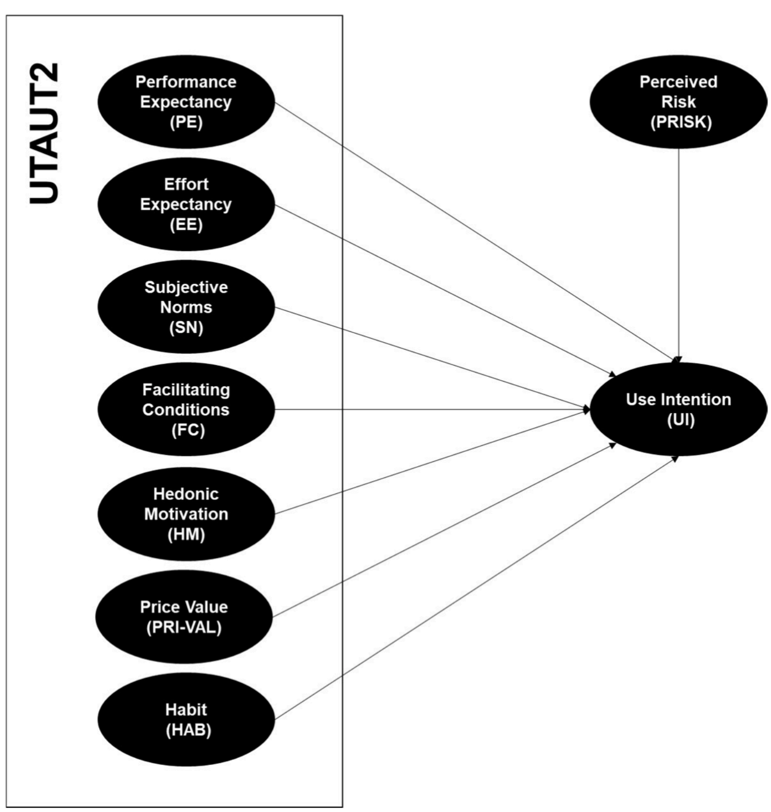

Fig. 1. Proposed conceptual model.

Table 3
Measurement scales.

Acronyms[a]	Statement	Source
PE1	BMPS[b] are of use to me in everyday life	Venkatesh et al. [47]
PE2	Using BMPS helps me carry out my transactions quickly	
PE3	Using BMPS improves my productivity	
PE4	I believe BMPS will help me achieve things that are important to me	
EE1	It is easy to learn how to use BMPS	Venkatesh & Bala (2008)
EE2	BMPS are clear and understandable to use	
EE3	Skills in using BMPS are easily acquired	
EE4	I find it easy to use BMPS	
SN1	People I consider important in my life think I should use BMPS	Venkatesh et al. [47]
SN2	Most of the people whose opinions I value think I should use BMPS	
SN3	I am expected by those closest to me to use BMPS to buy a product	
SN4	People close to me would agree that I should use BMPS to buy a product	
FC1	I have the necessary resources to use BMPS	Venkatesh et al. [47]
FC2	I have the necessary knowledge to use BMPS	
FC3	I can get help from others when I have difficulties using BMPS	
FC4	BMPS are compatible with other applications I use	
HM1	Using BMPS can be fun	Venkatesh & Bala [46]
HM2	Using BMPS is fun	
HM3	I enjoy using BMP applications	
PRI-VAL1	BMPS are reasonably priced	Venkatesh et al. [47]
PRI-VAL2	At the current price, BMPS provide good value	
PRI-VAL3	BMP applications are worth the money	
PRI-VAL4	BMP applications are beneficial to me	
HAB1	Using BMPS has become a habit	Venkatesh et al. [47]
HAB2	I must use BMPS	
HAB3	Using BMPS has become natural to me	
PRISK1	Other people may uncover information about my online transactions if I use BMPS	Liébana-Cabanillas et al. [84]
PRISK2	There is a high potential for monetary loss if I make my purchases using BMPS	
PRISK3	There is a significant risk in making my purchases using BMPS	
PRISK4	I consider making my purchases using BMPS to be a risky choice	
UI1	Assuming I had access to BMPS, I would intend to use them to make my purchases	Venkatesh & Bala [46]
UI2	Assuming I had access to BMPS, I would use them in the next few months	
UI3	Assuming I had access to BMPS, I would intend to use them frequently	

Note: (a) PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk, UI=Use intention; (b) BMPS=Biometric m-payment systems

correctly, a promotional video by the company was adapted to explain how this biometric payment system works. In the process of presenting the survey to the participants, we informed them that the video would contain a code that they had to input for some of the questions on the questionnaire. Only those responses that correctly indicated the code in question were used. According to Wells [85] and Liébana-Cabanillas et al. [86], information that has been processed, consciously or unconsciously, stimulates recall, which increases the likelihood that participants will remember the messages they have been shown, thus improving the reliability of the results.

To minimise the drop-out rate, we included information about the purpose of the research in the survey, together with a statement guaranteeing the anonymity of the respondents. In addition, we offered some small incentives, such as mugs and umbrellas featuring the university logo, and, at the end of the survey, awarded these to randomly selected participants. To reduce the occurrence of missing values, the participants were required to give their responses to all questions/statements before they could progress to the next page/end of the survey (otherwise, a notification would pop up).

Regarding the sample characteristics, 51.5 % were women, 76 % of the total were under 45 years of age, 46.5 % had studied at the higher education level and 63.8 % were in employed work. Table 4 presents the sample characteristics.

5. Data analysis and results

First, we used ordinary least squares (OLS) as a baseline model. Next, we applied partial least square structural equation modelling (PLS-SEM) to test the research hypotheses. PLS-SEM is considered to efficiently address a wide range of problems since it is less restrictive towards statistical assumptions (e.g., normality; [87]). This causal–predictive approach is suitable for predicting statistical models whose structures are designed to provide causal explanations [88], and for different types of analysis, including confirmatory research. In the present study, our analysis was based on goodness-of-fit [89] and also bootstrapping—a nonparametric method that can be equally applied via other SEM techniques [90].

We tested the proposed conceptual framework using SmartPLS 3 software in two stages: 1) to evaluate the measurement model (reliability and convergent and discriminant validity) and 2) to evaluate the structural model to test the research hypotheses. After testing for linearity vs. nonlinearity in the relationships identified in the structural model, we estimated an ANN-based model—such models being robust, flexible [91,92] and more accurate in the case of nonlinearity [92]. But the main deficiency of the ANN approach is that, due to its 'black box' operation, it cannot be used for causal relationship hypothesis testing [93]. For this reason, we used PLS-SEM to determine significant predictors of use intention, and, in a further step, we then used the confirmed predictors as inputs to the ANN model [94–97]. By means of this two-step process, we were able to rank the influence of the predictors more accurately because the ANN model takes into account nonlinearities among variables. A broad overview of the application of ANN models in technology acceptance studies is presented by Kalinic et al. (2021).

Table 4
Sample characteristics.

Variable	Number	Percentage of sample
Gender		
Male	1254	48.50 %
Female	1332	51.50 %
Age bracket (years)		
16–24	297	11.50 %
25–34	835	32.30 %
35–44	833	32.20 %
45–54	497	19.20 %
55–64	106	4.10 %
65–74	18	0.70 %
Educational level		
Primary education	134	5.20 %
Secondary education/Vocational training	1223	47.30 %
Higher education	1202	46.50 %
Other	26	1.00 %
Employment status		
Employed	1650	63.81 %
Actively seeking work	386	14.91 %
Student	207	8.02 %
Inactive: household workers	131	5.07 %
Inactive: retired	70	2.70 %
Other employment status	141	5.46 %
Net monthly household income		
Less than 1100 Euros	785	30.36 %
1101–1800 Euros	650	25.12 %
1801–2700 Euros	789	30.50 %
More than 2700 Euros	349	13.50 %
No answer/does not know	13	0.52 %

5.1. Testing of multivariate assumptions

Prior to conducting further data analyses, we assessed the multivariate assumptions of normality, linearity, multicollinearity and homoscedasticity [98]. The results of the one-sample Kolmogorov-Smirnov test [99], presented in Table 5, indicate the absence of normal distribution [99], since all 2-tailed asymptotic significance values were 0.000—that is, less than 0.05 [82,96]. Hence, we opted for PLS-SEM in this study because it has been shown to be robust under conditions of non-normality [100].

We performed an ANOVA to test the linearity of the relationships between variables [100,82], the results of which are presented in Table 6. The results show that there are linear relationships between the dependent (use intention) and independent variables, since all p-values are below 0.05. However, seven out of the eight relationships reveal a statistically significant deviation from linearity, which justified the use of the ANN model—a nonlinear artificial intelligence technique that reflects the structure and operation of the human brain. The only exception was the relationship between price value and use intention, albeit its p-value (0.054) was very close to the significance threshold (0.05).

Multicollinearity is a problem of high correlation between independent variables [101]. The results of the multicollinearity test performed on our model (see Table 7) indicate that there were no issues of multicollinearity, since all the Variance Inflation Factor (VIF) values were in the range of 1.065–3.562 (i.e., less than 10), and the tolerances were all higher than 0.10 [93,99].

Homoscedasticity, also known as homogeneity of variance, is usually assessed based on the dispersion of regression standardised residuals [99], which we analysed. Since the residuals were scattered evenly along a straight line, it can be concluded that the assumption of homoscedasticity was fulfilled [93,98].

Table 5
One-sample Kolmogorov-Smirnov test for normal distribution.

Item	N	Normal Parameters[a,b]		Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)
		Mean	Std. Dev.		
PEE1	2586	4.06	1.675	8.651	0.000
PEE2	2586	3.66	1.636	9.067	0.000
PEE3	2586	4.05	1.649	9.027	0.000
EE1	2586	4.67	1.663	8.397	0.000
EE2	2586	4.87	1.447	4.874	0.000
EE3	2586	5.06	1.524	8.698	0.000
SN1	2586	3.85	1.530	10.041	0.000
SN2	2586	3.51	1.554	9.675	0.000
SN3	2586	3.41	1.678	9.118	0.000
SN4	2586	3.68	1.571	10.060	0.000
FC1	2586	4.37	1.482	8.691	0.000
FC2	2586	4.44	1.409	9.439	0.000
FC3	2586	4.65	1.458	8.132	0.000
HM1	2586	4.60	1.353	9.137	0.000
HM2	2586	4.63	1.373	9.307	0.000
PRI-VAL1	2586	4.10	1.399	10.932	0.000
PRI-VAL2	2586	4.24	1.396	10.706	0.000
HAB1	2586	3.57	1.683	8.389	0.000
HAB2	2586	3.57	1.705	8.429	0.000
PRISK1	2586	4.08	1.653	8.534	0.000
PRISK2	2586	3.89	1.586	8.345	0.000
PRISK3	2586	4.09	1.600	8.160	0.000
PRISK4	2586	4.15	1.650	7.644	0.000
UI1	2586	4.15	1.615	9.258	0.000
UI2	2586	4.46	1.496	9.019	0.000

(a) Test distribution is normal; (b) Calculated from data.

5.2. Reliability and validity analysis

We evaluated the measurement model by analysing its reliability and convergent and discriminant validity. The reliability analysis included three indicators of internal consistency: Cronbach's alpha (CA; [102]), the Rho coefficient and composite reliability (CR; [103]). The values for all three tests were above the recommended minimum value of 0.7. We assessed CR using average variance extracted (AVE). The AVE indicates the amount of variance a variable obtains from its indicators relative to the amount of variance caused by measurement error. All the AVE values were above the recommended minimum value of 0.5 [104]. Table 8 lists these values for each variable, along with the mean of each item and the outer loadings (i.e., the loads estimated for the relationships in reflective measurement models).

In this study, the presence of nonresponse bias was detected. To address this issue, we conducted a multigroup analysis, following the approach outlined by Hair et al. [105]. We compared the group of respondents who completed the survey promptly (within the first 5 days of issue) with the group of respondents who completed it later. The results indicated that there were no statistically significant differences between these two groups in terms of all variables ($p > 0.05$). Consequently, it can be concluded that the potential impact of nonresponse bias on the sample data is likely to be minimal or negligible [106].

Next, we assessed discriminant validity by comparing the squared AVE with the intercorrelation scores. Discriminant validity is achieved if the squared AVE of a variable is greater than the intercorrelation with other variables [107]. We further checked discriminant validity by applying the heterotrait-monotrait (HTMT) ratio. Henseler et al. [108] suggest that a HTMT ratio score above 0.90 indicates a discriminant validity issue. The HTMT ratio scores were all below the threshold, indicating that discriminant validity was achieved (see Table 9).

5.3. Testing the hypotheses using OLS

First, we tested the research hypotheses by comparative analysis of the coefficients obtained by OLS, using IBM SPSS v20 as a simulation tool. The results, presented in Table 10, confirm that none of the initial eight hypotheses derived from the extended UTAUT2 model could be rejected—that is, that all eight predictors have a statistically significant influence on the dependent variable (use intention).

The most influential predictors according to the OLS findings are performance expectancy ($\beta_{PE \to UI}$=0.321, p-value=0.000), effort expectancy ($\beta_{EE \to UI}$=0.177, p-value=0.000) and facilitating conditions ($\beta_{FC \to UI}$=0.150, p-value=0.000), followed by hedonic motivation ($\beta_{HM \to UI}$=0.120, p-value=0.000), subjective norms ($\beta_{SN \to UI}$=0.100, p-value=0.000) and habit ($\beta_{HAB \to UI}$=0.112, p-value=0.000). The least influential predictors as per OLS are risk ($\beta_{PRISK \to UI}$= -0.084, p-value=0.000) and price value ($\beta_{PRI\text{-}VAL \to UI}$=0.065, p-value=0.006).

We assessed the quality of the OLS model using the values of adjusted R^2 (which was 0.724) and normalised root mean squared error (RMSE), which was 0.1292. Both values are acceptable, meaning that OLS can be accepted as a valid baseline model.

5.4. Testing the hypotheses using SEM

Next, we analysed the structural model. First, we tested the research hypotheses by conducting comparative analysis of the structural coefficients. We performed a bootstrapping analysis on a total of 5000 subsamples randomly drawn from the original dataset, which showed that none of the eight hypotheses could be rejected. All hypotheses that are part of the UTAUT2 model and that proposed a positive relationship with the dependent variable (use intention) found empirical support. The hypotheses and the corresponding results were as follows: H1 (performance expectancy) ($\beta_{PE \to UI}$=0.305, p-value=0.000), H2 (effort expectancy) ($\beta_{EE \to UI}$=0.185, p-value=0.000), H3 (subjective norms) ($\beta_{SN \to UI}$=0.095, p-value=0.000), H4 (facilitating conditions)

Table 6
ANOVA test of linearity.

Relationship		Sum of Squares	df	Mean Square	F	Sig.
UI * PE	Linearity	3319.799	1	3319.799	3767.861	0.000
	Deviation from linearity	62.623	17	3.684	4.181	0.000
UI * EE	Linearity	2662.181	1	2662.181	2426.234	0.000
	Deviation from linearity	222.401	69	3.223	2.938	0.000
UI * SN	Linearity	2624.259	1	2624.259	2297.745	0.000
	Deviation from linearity	94.980	23	4.130	3.616	0.000
UI * FC	Linearity	2886.810	1	2886.810	2717.682	0.000
	Deviation from linearity	30.602	17	1.800	1.695	0.037
UI * HM	Linearity	1429.142	1	1429.142	884.285	0.000
	Deviation from linearity	56.653	11	5.150	3.187	0.000
UI * PRI-VAL	Linearity	2564.041	1	2564.041	2158.097	0.000
	Deviation from linearity	23.133	11	2.103	1.770	0.054
UI * HAB	Linearity	2813.772	1	2813.772	2608.586	0.000
	Deviation from linearity	55.003	11	5.000	4.636	0.000
UI * PRISK	Linearity	196.924	1	196.924	94.765	0.000
	Deviation from linearity	125.391	23	5.452	2.624	0.000

Note: PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk, UI=Use intention

Table 7
Multicollinearity test: Non-standardised and standardised coefficients[a].

Model	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	0.352	0.084	–	4.182	0.000	–	–
PE	0.288	0.019	0.299	14.914	0.000	0.281	3.562
EE	0.206	0.017	0.203	11.938	0.000	0.389	2.574
SN	0.098	0.019	0.096	5.192	0.000	0.330	3.027
FC	0.130	0.021	0.118	6.101	0.000	0.300	3.334
HM	0.126	0.014	0.112	8.974	0.000	0.724	1.381
PRI-VAL	0.066	0.019	0.061	3.466	0.001	0.368	2.718
HAB	0.100	0.018	0.112	5.603	0.000	0.281	3.557
PRISK	-0.082	0.011	-0.081	-7.398	0.000	0.939	1.065

[a] Dependent variable: Use intention (UI); Note: PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk

($\beta_{FC\rightarrow UI}$=0.125, p-value=0.000), H5 (hedonic motivation) ($\beta_{HM\rightarrow UI}$=0.114, p-value=0.000), H6 (price value) ($\beta_{PRI\text{-}VAL\rightarrow UI}$=0.065, p-value=0.006) and H7 (habit) ($\beta_{HAB\rightarrow UI}$=0.112, p-value=0.000) (supported). Finally, H8 posited a negative effect of perceived risk on use intention, which cannot be rejected ($\beta_{PRISK\rightarrow UI}$=-0.084, p-value=0.000).

We also assessed the predictive ability of the model by determining the squared multiple correlation coefficient (R^2). The R^2 value for use intention was 0.708, meaning that it explains a high proportion of the variance of the model. Furthermore, we examined the standardised root mean square residual (SRMR) value [108] to test the difference between the observed correlation and the predicted correlation as an indicator of model fit. A value of less than 0.08 is considered acceptable. The model proposed in this study yielded a value below this threshold (0.046). We also evaluated effect size (f^2) after reviewing research from Chin [109], who indicated that f^2 values of 0.02–0.15, 0.15–0.35 and 0.35 or higher suggest that an independent or exogenous latent variable has a small, moderate or large effect, respectively, on a dependent latent variable. The relationship between the variables in the present study was found to exert a significant effect, and the lowest value with regard to f^2 pertained to the relationship between perceived value and use intention. Finally, we assessed the predictive relevance of the model using Stone-Geisser's Q^2 value. According to Chin [109], a model demonstrates good predictive relevance when its Q^2 value is greater than zero. Thus, the present value can be considered adequate. Table 10 summarises all of these results.

5.5. Neural network analysis

Although very useful, PLS-SEM and most of the other conventional statistical techniques assume linearity, meaning that they cannot take into account any nonlinearity between variables [95]. The results of the ANOVA, presented in Table 6, confirmed the existence of significant nonlinearities among variables. Hence, we concluded that a technique capable of dealing with nonlinear effects was required, such as ANN. ANNs enable noncompensatory decision processes to be studied [110], where the shortfall in one of the predictors cannot be compensated by improving another adoption predictor [62]. The ANN approach has also been shown to be more accurate and to possess higher predictive power than traditional, linear regression techniques [100]. Furthermore, the application of an additional method improves the validity of, and confidence in, previously obtained results [62].

In particular, the ANN model presented in this study is a multilayer perceptron (MLP) with a feed-forward back-propagation training algorithm [62,93]. In general, such models consist of several layers (one input layer, one or more hidden layers, and one output layer) of highly interconnected neurons [91]. The choice of the number of input and output neurons is quite straightforward (they are equal to the number of predictors and dependent variables, respectively), but there are no strict rules regarding how to determine other hyperparameters of ANN models, such as the number of hidden layers, hidden neurons, choice of activation function and so on (Kalinic et al., 2021).

The choice of the number of hidden layers depends on the complexity of the problem. ANN models with one hidden layer (shallow ANNs) are sufficient to model any continuous function, whereas ANNs with two

Table 8
Reliability and convergent validity of the measures.

Variables	Mean	Loadings	CA	Rho	CR	AVE
Performance expectancy						
PE1	4.06	0.917	0.917	0.921	0.948	0.858
PE2	3.66	0.950				
PE3	4.05	0.905				
PE4	4.10	0.937				
Effort expectancy						
EE1	4.67	0.862	0.9021	0.912	0.938	0.836
EE2	4.94	0.934				
EE3	5.06	0.944				
EE4	4.88	0.932				
Subjective norms						
SN1	3.85	0.906	0.934	0.938	0.953	0.835
SN2	3.51	0.932				
SN3	3.41	0.890				
SN4	3.68	0.928				
Facilitating conditions						
FC1	4.37	0.930	0.921	0.923	0.950	0.863
FC2	4.44	0.934				
FC3	4.65	0.924				
FC4	4.30	0.938				
Hedonic motivation						
HM1	4.60	0.942	0.915	0.915	0.959	0.922
HM2	4.63	0.957				
HM3	4.65	0.956				
Price value						
PRI-VAL1	4.10	0.960	0.940	0.940	0.971	0.943
PRI-VAL2	4.24	0.967				
PRI-VAL3	4.23	0.965				
PRI-VAL4	4.20	0.958				
Habit						
HAB1	3.57	0.968	0.952	0.953	0.977	0.955
HAB2	3.59	0.976				
HAB3	3.61	0.975				
Perceived risk						
PRISK1	4.08	0.805	0.925	1.009	0.945	0.810
PRISK2	3.89	0.904				
PRISK3	4.09	0.945				
PRISK4	4.15	0.938				
Use intention						
UI1	4.15	0.951	0.891	0.891	0.948	0.902
UI2	4.46	0.959				
UI3	4.35	0.953				

Note: CA=Cronbach's alpha, CR=Composite reliability, AVE=Average variance extracted, PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk, UI=Use intention

hidden layers can be used to model even discontinuous functions [111]. ANN models with two or more hidden layers are called deep ANN models, as they enable deep learning and modelling of more complex relationships ([98]; Kalinic et al., 2021), but they also require more data for training and testing. Although Kalinic et al. (2021) proved that, in the case of relatively simple research models, the introduction of a second hidden layer does not deliver any improvement in terms of accuracy, in our case, the high number of predictors and nonlinear relationships led us to select the deep learning ANN approach (Alharbi and Sohaib, 2020; [98]). This provided two hidden layers in the neural network and, thus, a greater degree of precision. We determined the number of neurons in hidden layers using simulation software—SPSS v20 [95,112]—and we used sigmoid as an activation function in both hidden and output layers [50,96]. The deep learning ANN model is presented in Fig. 2.

The complexity of the prediction model significantly influences the minimum dataset size necessary to train the model: the more complex the model proposed, the more samples required to train the ANN model. The deep learning ANN model presented in Fig. 2 has 109 adjustable parameters (96 neuron weights and 13 biases). Of the dataset of 2586 samples, 90 % were used for the training of the ANN model and 10 % for its testing [113,114]. Following Widrow's rule-of-thumb ([111], p. 329), to attain an estimation error of 10 %, for example, the number of training examples should be 10 times bigger than the number of adjustable parameters in the ANN model [62]. In our case, using the same rule-of-thumb, we estimated that, based on 109 adjustable parameters and 2327 training examples, our model would present an estimation error lower than 5 %. Therefore, we concluded that our dataset was large enough to apply ANN.

One of the potential problems associated with ANNs is overfitting [86], which occurs when the model 'memorises' data from the training sample and loses the ability to generalise when used with previously unseen data. To avoid this problem, we performed 10-fold cross validation [95,115]. A common measure of the prediction accuracy of ANN models is RMSE [91,99] (Table 11).

The low RMSE values presented in Table 11 indicate good reliability and high prediction accuracy for the proposed model [101,50]. Finally, we further evaluated the performance of the ANN model by determining its goodness-of-fit coefficient R^2 [116,100], using the following formula:

Table 10
Coefficients by OLS analysis.

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.362	0.079		4.579	0.000
PE	0.299	0.018	0.321	16.453	0.000
EE	0.177	0.017	0.177	10.540	0.000
SN	0.098	0.018	0.100	5.578	0.000
FC	0.160	0.021	0.150	7.667	0.000
HM	0.132	0.013	0.120	9.847	0.000
PV	0.072	0.018	0.068	3.904	0.000
HAB	0.065	0.017	0.076	3.853	0.000
RISK	-0.072	0.010	-0.074	-6.928	0.000

Note: PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk, UI=Use intention

Table 9
Discriminant validity of the measures: HTMT ratios.

	EE	FC	HAB	HM	UI	PE	PRISK	PRI-VAL	SN
EE	*0.914*								
FC	0.841	*0.929*							
HAB	0.568	0.678	*0.977*						
HM	0.522	0.502	0.402	*0.960*					
UI	0.744	0.790	0.765	0.558	*0.950*				
PE	0.663	0.768	0.837	0.473	0.848	*0.926*			
PRISK	0.075	0.089	0.199	0.053	0.204	0.125	*0.900*		
PRI-VAL	0.645	0.742	0.752	0.467	0.736	0.725	0.207	*0.971*	
SN	0.564	0.680	0.814	0.435	0.747	0.812	0.100	0.724	*0.914*

Note: PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk, UI=Use intention

Table 10a
General model resolution by SmartPLS using the PLS algorithm and bootstrapping (5000 subsamples).

Nº	Research hypotheses	Path Coefficient	Std Dev.	t-value	p-value	f^2
H1(+)	PEàUI	0.305	0.026	11.832	**0.000**	0.103
H2(+)	EE àUI	0.185	0.022	8.276	**0.000**	0.045
H3(+)	SNàUI	0.095	0.021	4.495	**0.000**	0.010
H4(+)	FCàUI	0.125	0.027	4.589	**0.000**	0.021
H5(+)	HMàUI	0.114	0.016	7.069	**0.000**	0.033
H6(+)	PRI-VALàUI	0.061	0.022	2.755	**0.006**	0.004
H7(+)	HABàUI	0.112	0.024	4.748	**0.000**	0.007
H8(-)	PRISKàUI	-0.084	0.012	7.095	**0.000**	0.022

UI: Q^2=0.633, R^2=0.708, SRMR=0.046

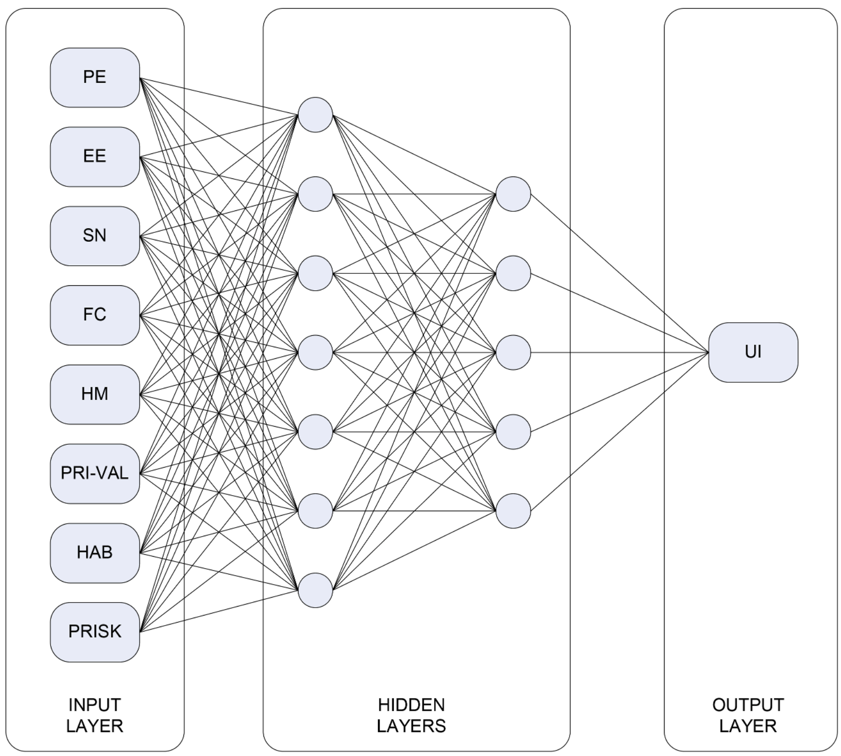

Fig. 2. Estimated deep learning ANN model
Note: PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk, UI=Use intention.

Table 11
RMSE values of ANNs.

Network	Inputs: PE, EE, SN, FC, HM, PRI-VAL, HAB, PRISK Output: UI	
	Training	Testing
1	0.095	0.092
2	0.096	0.083
3	0.093	0.098
4	0.097	0.088
5	0.094	0.102
6	0.094	0.088
7	0.096	0.087
8	0.095	0.104
9	0.094	0.098
10	0.095	0.098
Mean	0.095	0.094
Standard deviation	0.001	0.007

Note: PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk, UI=Use intention

$$R^2 = 1 - \frac{RMSE}{s_y^2},$$

where s_y^2 is the variance of the desired output. The value $R^2 = 0.957$ indicates that the ANN acceptance model explains 95.7 % of the variance of use intention (model output), which is a significant improvement on the PLS-SEM results.

Finally, we performed a sensitivity analysis of the ANN model to determine the importance of each predictor. The importance of a predictor measures the significance of the changes in the output caused by changes in different predictors [62]. The normalised importance is calculated by dividing the importance values of each predictor by the largest importance value [91]. Values for the relative and normalised importance of the ANN model are presented in Table 12.

The most significant predictor of use intention is PE (average importance: 0.256), followed by EE (0.175), FC (0.134) and HM (0.104), which is in line with SEM-PLS findings. Next, the ANN model predicts that SN (0.099) has a more significant impact than HAB (0.089), which differs from SEM-PLS results. Finally, the two least influential predictors were PRISK (0.087) and PRI-VAL (0.057), which was also predicted by SEM-PLS findings. These minor differences between the ANN and SEM-

Table 12
Neural network sensitivity analysis.

Network	Relative importance							
	PE	EE	SN	FC	HM	PRI-VAL	HAB	PRISK
1	0.213	0.152	0.095	0.147	0.1	0.087	0.105	0.101
2	0.247	0.146	0.127	0.138	0.114	0.058	0.083	0.088
3	0.32	0.17	0.078	0.097	0.118	0.033	0.11	0.075
4	0.236	0.222	0.162	0.133	0.091	0.007	0.013	0.136
5	0.215	0.189	0.108	0.128	0.091	0.051	0.099	0.119
6	0.284	0.184	0.073	0.103	0.114	0.071	0.103	0.068
7	0.26	0.196	0.088	0.132	0.108	0.068	0.083	0.065
8	0.219	0.118	0.053	0.191	0.099	0.09	0.18	0.051
9	0.312	0.213	0.117	0.102	0.123	0.036	0.043	0.053
10	0.255	0.155	0.087	0.166	0.082	0.066	0.072	0.117
Average importance	0.256	0.175	0.099	0.134	0.104	0.057	0.089	0.087
Normalised importance (%)	100.0	68.1	38.6	52.2	40.6	22.1	34.8	34.1

Note: PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk

PLS findings can be explained by the higher prediction accuracy of the ANN model and its capacity to consider any nonlinear relationships among the variables [50,62]. A detailed comparison of OLS, SEM-PLS and ANN findings is presented in Table 13 [117].

6. Conclusions, implications, limitations and future research directions

6.1. Discussion

In recent years, consumer behaviour has rapidly changed towards the use of alternative payment systems, such as virtual bank cards and m-payment with NFC or QR codes. To tighten security measures, these payment systems can now also integrate biometric authentication technologies—an option that is commercially available [9,10] but not yet widely implemented.

After reviewing the relevant research on UTAUT2 (with performance expectancy, effort expectancy, subjective norms, facilitating conditions, hedonic motivation, price value and habit as exogenous factors) and its later extensions, our research extends this modelling further with perceived risk, which is considered one of the most important variables in the adoption of m-payment.

First, a model obtained with PLS-SEM showed adequate psychometric properties for both the measurement model (in terms of reliability and convergent and discriminant validity) and the structural model used to test the proposed research hypotheses. The estimated model shows that performance expectancy was the most important determinant. The results show that, to the extent that an individual believes in the m-payment system—that is, believes in the benefits and advantages of using it—this positive perception will contribute to increasing their use intention towards it. The other factors were also important, albeit to a lesser extent. The model also demonstrated good explanatory relevance. Specifically, the results of our research improve on the results of Odusanya et al. [118] and Alalwan et al. [119] in terms of the percentage of variance explained (67.5 % and 64 %, respectively, vs. 70.8 % in our research), which confirms the explanation of the proposed objectives.

Table 14 presents a comparison of similar research studies related to m-payment that have employed the UTAUT2 model as a theoretical framework. As can be seen, the results are aligned with the recent proposals of Al-Okaily et al. [120] and Migliore et al. (2020), which reinforces the generalisability of the findings obtained.

H1 finds empirical support, since performance expectancy has a significant and positive relationship with use intention, which means that for users of BMPS, higher performance will lead to higher use intention. H2 also finds empirical support. In this case, users believe that BMPS will be easy to use and will require no additional effort, which will consequently improve use intention. H3 is also confirmed, showing that the favourable opinions, comments and experiences of friends, family and others in the user's environment regarding the use of the proposed payment systems will increase their intention to use them. H4, which proposed a positive relationship between facilitating conditions and use intention, was also supported: users' knowledge, skills and resources will contribute to improving their use intention towards BMPS. Turning to H5, a positive relationship is confirmed for hedonic motivation—that is, enjoyment stimulates use intention, based on feelings of positivity. Regarding the price value of using BMPS (H6), we also conclude that there is a significant and positive relationship with use intention. H7 also finds empirical support: repeated learning or a habit that derives from similar behaviours (e.g., habitual use of payment systems other than traditional ones) improves the intention to use BMPS. Finally, H8 is verified, confirming a negative relationship between the perceived risk of using BMPS and use intention. The negative effect was only to a limited degree, however, as this type of payment system is considered more secure than others, as noted earlier.

Second, the significant predictors that had been determined were

Table 13
Comparison of OLS, PLS-SEM, and ANN results.

Relationships	OLS stand. coef. (Beta)	PLS-SEM path coef.	ANN normalised relative import. (%)	OLS ranking based on stand. coef.	PLS-SEM ranking based on path coef.	ANN ranking based on normalised relative import.
PE → UI	0.321	0.305	100	1	1	1
EE → UI	0.177	0.185	68.1	2	2	2
FC → UI	0.150	0.125	52.2	3	3	3
HM → UI	0.120	0.114	40.6	4	4	4
SN → UI	0.100	0.095	38.6	5	6	5
HAB → UI	0.076	0.112	34.8	6	5	6
PRISK → UI	-0.074	-0.084	34.1	7	7	7
PRI-VAL → UI	0.068	0.061	22.1	8	8	8

Note: PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk, UI=Use intention

Table 14
Comparative analysis of recent research studies on m-payment.

Authors	PE	EE	SN	FC	HM	PV	HAB	RISK
Al-Okaily et al. [120]	0.217	**0.020** (n.s.)	0.298	**-0.063** (n.s.)	–	0.111		**0.238** (n.s.)
Bailey et al. [121]	0.270	0.730		**-0.020** (n.s.)	–	–	–	–
Gupta and Arora [52]	0.230	0.200	**0.120** (n.s.)	0.240	**0.140** (n.s.)	–	0.340	–
Kalinic et al. [95]	–	–	–	0.403	–	–	0.205	–
Liébana-Cabanillas et al. [75]	–	–	–	–	–	–	–	-0.184
Liébana-Cabanillas et al. [82]	–	–	0.246	–	**-0.039** (n.s.).	–	–	-0.070
Linge et al. [122]	0.165	0.187	0.169	0.312	0.141	–	–	
Migliore et al. (2020)	0.408	0.127	0.079	0.122	0.126	**0.056** (n.s.)	–	**-0.009** (n.s.)
Morosan and DeFranco [53]	0.380		0.15	0.090	0.199	–	0.188	–
Widyanto et al. [54]	**0.070** (n.s.)	0.392	0.24	**0.066** (n.s.)	0.340	–	–	–

Note: PE=Performance expectancy, EE=Effort expectancy, SN=Subjective norms, FC=Facilitating conditions, HM=Hedonic motivation, PRI-VAL=Price value, HAB=Habit, PRISK=Perceived risk, UI=Use intention; n.s.: not significant; -: relationships not proposed in the reviewed research

used as inputs to the ANN model, with which we were able to rank the influence of the predictors more accurately because such models take into account nonlinear relationships among variables. In our case, seven out of the eight relationships presented a statistically significant deviation from linearity. The goodness-of-fit coefficient indicated that the ANN model explained more than 95 % of the variance of intention, which is a significant improvement on the PLS-SEM results.

In general, the results of the ANN analysis confirmed almost all the SEM findings, but they also showed a slightly different order of influence of the less significant predictors. These minor differences between the analytical approaches we applied may be explained by the greater prediction accuracy of the ANN model and its capacity to take nonlinear relationships among variables into account [50,62].

6.2. Theoretical implications

This study contributes to the current state of the art relating to (1) understanding BMPS [31], (2) a modification of the UTAUT2, with the addition of PRT [123], and (3) a comparative analysis of two techniques (PLS-SEM and ANN) [117] to analyse use intention towards this novel payment system.

After performing the SEM analysis, this research found that the most significant variables impacting on use intention were performance expectancy, effort expectancy, hedonic motivation and habit. In general, the results show that performance expectancy enables consumers to perceive BMPS as useful, whereas effort expectancy enables the systems to be perceived as easy to use. These findings are mostly in line with those of previous research. Gupta and Arora [52] confirmed that performance expectancy, effort expectancy and habit significantly predicted behavioural intention, which, in turn, significantly predicted m-payment system use behaviour; in contrast, both social influence and hedonic motivation were found to be weak predictors of behavioural intention. Morosan and DeFranco [53] also found that performance expectancy was the strongest predictor of intentions, whereas hedonic motivations, habit and social influences had relatively low effects. In particular, our results indicate that the convenience or ubiquity of mobile devices—such as the fact that their physical dimensions fit most pockets and they are increasingly used for multiple purposes in daily life—is one of the main advantages of the different applications of mobile commerce, as it enables customers to make transactions at virtually any time and from virtually anywhere [124]. In general, performance expectancy is of critical importance for future use, as it improves users' work performance, productivity and effectiveness by positively influencing their willingness to continue using mobile services in the future. Perceived risk is also an important predictor of use intention because users who perceive a higher level of security are more inclined to accept these new m-payment methods.

Although, overall, the results of the ANN analysis confirmed many of the SEM findings, they did present a slightly different order of influence, in terms of the determinants of UI, for two specific predictors with low significance: social norms and habit. Habit appeared to be less relevant than social norms, according to the ANN results, whereas in the PLS-SEM estimation, the order was inversed. These and other minor differences between the SEM and ANN results may be explained by the higher performance of the ANN models, thanks to their nonlinear and non-compensatory nature.

6.3. Managerial implications

A significant increase in the adoption and usage of biometrics is being seen, given that such systems or technologies are versatile enough for most users and offer better security than other m-payment systems (e.g., QR or NFC).

The present study shows that hedonic motivation exerts a lower influence than other (utilitarian) motivations, such as performance expectancy, effort expectancy or facilitating conditions. This confirms that such systems offer a *practical* solution that facilitates *safe* day-to-day monetary transactions; these should be the arguments used by those responsible for the promotion and/or take-up of these systems.

Based on these outcomes, biometric authentication in m-payment systems should be promoted as an integral part of the lifestyle of modern consumers when performing everyday financial operations. Promotional campaigns should emphasise their usefulness and primary benefits in terms of improved performance, such as more secure transactions and faster shopping, to capture consumers' attention and increase the chances of their adopting payment methods that feature innovative biometric identification. Online brochures and guides providing a detailed overview of all the benefits of using m-payment and all the necessary steps for its implementation in different transactions should also be offered to consumers.

This research proposed the inclusion of risk analysis as a modification of the UTAUT2 model, as perceived risk is considered by the scientific literature to be one of the most influential variables. Notwithstanding, the results confirm that although its relationship in the proposed model is significant, it is not as important as in other payment systems analysed in previous studies [123]. We believe this reflects users' greater sensitivity to the high level of security offered by this type of payment system.

Both financial entities and developers of smartphone applications must prioritise security in the context of m-payment, investing accordingly, while making users aware of the secure methods they have implemented [125]. Security-related concerns regarding m-payment can become a severe deterrent to the adoption of such applications [125]. Consumers should perceive m-payment to be trustworthy, and m-payment providers must be perceived as reliable, because when customers perceive these payment systems to be secure and private, they are more likely to trust, use and recommend them. Hence, trust can be a robust construct for predicting use (continuance) behaviour in m-payment systems [126,127]. Therefore, marketing campaigns should emphasise the security measures and safeguards used to prevent information theft and financial losses while encouraging customers to use m-payment as a safe alternative in their day-to-day financial activities.

To provide a high level of security for transactions, biometric technology providers should adopt advanced measures, such as new encryption methods, while also supporting the most up-to-date authentication methods, such as fingerprint, iris or face identification, through dedicated sensors available on most mobile devices. To help increase consumer confidence, service providers may also make a prominent display of certifications or verification seals (e.g., VeriSign/ Symantec or TRUSTe), which indicate that the system and service have both been verified by trusted organisations. Consumers will then be more likely to perceive mobile transactions as a less uncertain and risky activity and will be more motivated to trust in m-payment.

We also observed that subjective norms, habit, perceived risk and price value exerted a higher influence than other factors, mainly due to the fact that this is a new service of which the consumer has no personal experience, and trust in third parties (friends and relatives) is still influential. Therefore, firms should stimulate consumers' external influences through various marketing campaigns to create a positive environment to help encourage the use of biometrics in m-payment. Harnessing opinions shared by third parties, usually through social media interactions but also through other communication channels, could become a powerful strategy for promoting the greater security offered by m-payment and stimulating its adoption. In addition, to obtain better results faster, it is important to achieve the good opinion of leaders and influencers in this process.

The opportunities offered by biometric payment systems will also allow public administration bodies and, indeed, any type of organisation to minimise waiting times for users when making any payment, improve service quality and, in turn, maximise user satisfaction.

In relation to the ongoing challenges generated by the COVID-19 pandemic, the biometric type of payment system can reduce (or entirely eliminate) the need for the consumer and the vendor to physically handle cash, payment terminals or cards. As there is no physical contact between buyer and seller, this approach offers improved safety by completely avoiding possible contagion through contact. In this respect, it is recommended that interested organisations encourage users to share their positive experiences of BMPS with their friends and social groups. If the aim is to improve take-up of such payment methods, potential users who are more fearful of virus contagion will take into account the opinion of their social group, so positive reviews about the usefulness and reliability of these systems are essential. Encouraging existing users to share their positive experiences with these payment methods on their own social networks will therefore help the service become mainstream more quickly as the message spreads throughout their social group. Inviting users to share their opinions on the organisation's, website, online forums or blogs will also help in this process.

The adoption of BMPS holds significant implications for business management. The inclusion of these authentication technologies in mobile payment processes offers a range of advantages in terms of security, convenience and user experience. They provide businesses with an opportunity to enhance transaction security and mitigate risks associated with fraud and identity theft. By requiring biometric authentication, an additional layer of protection is established, making identity theft and unauthorised access to user accounts more challenging for fraudsters.

Furthermore, these systems offer a faster and more convenient payment experience for customers. By eliminating the need to remember passwords or carry physical cards, biometric payments streamline the transaction process, which can lead to increased customer satisfaction and loyalty.

However, the adoption of BMPS also presents drawbacks and additional considerations for management. Addressing user privacy concerns and data protection is crucial, ensuring that appropriate standards are met and robust security measures are implemented. Additionally, investment in technological infrastructure is required to enable biometric authentication at point-of-sale terminals and payment platforms.

In summary, the implementation of BMPS has significant implications for business management. By improving security and enhancing the user experience, these systems offer substantial benefits, albeit requiring careful attention to privacy and technological infrastructure. The proper adoption of these systems can unlock new business opportunities and strengthen the competitive position of firms in the electronic payment market.

6.4. Limitations and potential future research avenues

Despite its multiple contributions, this study presents a number of limitations that point to potential avenues for further research. First, our study assesses intention to use m-payment and the influencing factors behind use intention in a nascent or growing market by studying a user sample exclusively comprising Spanish participants. However, this study could be used as a basis for research in other countries in which the level of adoption and acceptance of biometric m-payment technology is similar to that of Spain, examining the cultural differences at play.

We conducted a comprehensive literature review and identified a series of variables to extract a partial behavioural model that closely matches reality, but additional variables could have been included to achieve an even more comprehensive understanding of the adoption of these new advanced payment systems, such as perceived compatibility, personal innovativeness [86], perceived similarity and entitativity, or trust in online/m-payments [126]. Taking into account the original research behind the UTAUT2, other possible influencing factors, such as the gender of respondents and variables such as age and experience level, could be included in future analyses or even in the creation of new constructs based on the proposals of MacKenzie et al. [128].

The results of our research are only applicable to a general type of biometric authentication system. To achieve greater external validity, a comparative study could be conducted on other methods available on the market. This would provide both a categorisation and a use profile for each payment system, including the different types of biometric authentication technologies. Each user may even prefer a different authentication system, depending on the device in question.

Finally, the transversal nature of the data collection method employed in our research impedes a proper assessment of the behavioural evolution of users. A longitudinal approach would be even better suited, in this regard, since it would enable the reliability and strength of the different relationships and constructs proposed in this study to be tested while examining behaviour over time.

CRediT authorship contribution statement

Francisco Liébana-Cabanillas: Conceptualization, Data curation, Formal analysis, Methodology. **Zoran Kalinic:** Conceptualization, Data curation, Formal analysis, Methodology. **Francisco Muñoz-Leiva:** Supervision, Validation. **Elena Higueras-Castillo:** Supervision, Validation.

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