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A comprehensive view of biometric payment in retailing: A complete study from user to expert

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ABSTRACT

The new financial and commercial scenario driven by technological advances has undergone a rapid reconfiguration in the recent years. Innovation has generated new payment alternatives that are transforming the concept of money and payment habits among consumers. One of the most novel payment systems nowadays is known as biometric payment. Improved payment systems will improve retailing and consumer services. The aim of this study is to develop an analysis of biometric payment based on two complementary studies. In the first one, the variables predicting the intention to use this technology are determined on a sample of 1905 potential users by means of different feature selection methodologies from artificial intelligence in a holistic model that integrates the principles of the UTAUT2 model, the General Risk Theory, and the Trust Theory. In the second study, two panels of Fintech industry experts compare these results. The overall insights obtained show that perceived risk, trust, and social influence are the variables that, from the experts' experience, users consider most important when employing this technology. This research provides useful information for financial and business decision-makers in companies interested in commercializing this type of technology.

1. Introduction

The arrival of credit and debit cards allowed for a revolution in the way the banking system operated, boosting a society where payments could be made without the need for physical currency (Ramos de Luna et al., 2019). From then until today, financial institutions have employed many technologies to facilitate payments for their customers (Bojjagani et al., 2023). Among the most innovative payment systems, we highlight biometric payment systems (Hu et al., 2023).

Biometric payments are an authentication system for transactions that relies on the biometric information of each customer. Instead of using a PIN code to authorize the payment, it is based on the customer's own biometric identification features, such as fingerprint, voice, facial recognition, etc. (Clodfelter, 2010; Sulaiman and Almunawar, 2022). This type of payment systems usually has two variants. The first is a hybrid system that combines traditional methods, like chip cards, and biometric data. The second variant refers to systems that only require biometric information to efficiently complete a transaction.

Nowadays, the majority of credit cards have a magnetic stripe or a chip, which allows us to identify each customer. However, according to a recent report from Juniper Research (2023a), the future of electronic payments will be no longer tied to plastic cards or smartphones. Instead, it will be linked to the customer's fingerprints or even their face, serving as a replacement for the previous banking security systems. This innovative project, called "Visa Ready for Biometrics", will enable a customer to place their finger on a sensor, initiating a comparison between their actual fingerprint and the one saved on the card. This aims to authenticate the transaction securely. This new technology will enhance the security and speed of transactions in the commerce sector.

According to Juniper Research (2023b), global biometric payment data for the year 2023 indicates a substantial rise in the adoption of biometric technology for financial transactions. Recent research forecasts that the international biometric payment market is poised to attain a value of $103.14 billion by 2026, exhibiting a robust compound annual growth rate (CAGR) of 16.8% from 2019 to 2026.

The transition to biometric payment systems in the retail sector does not only constitute a tactical move toward modernization but also represents a crucial strategic decision to enhance customer experience. The

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convergence of factors such as reinforced transactional security, more efficient operations, and alignment with prevailing digital trends endows this transition with intrinsic value, elevating it to the status of being essential in the context of an increasingly competitive market. Upon closer analysis, heightened security associated with biometric payments emerges as a preeminent factor, mitigating risks and bolstering confidence for both consumers and retailers. Biometric uniqueness, whether through facial recognition or fingerprinting, does not only set a higher standard for authentication but also acts as an effective antidote against fraud threats and identity theft, historically significant concerns in the realm of retail. Furthermore, enhanced operational efficiency is a key component of the transition to biometric payments. The elimination of physical and temporal barriers associated with cash or cards significantly streamlines transactions, reducing waiting times and optimizing business processes. This agility does not only improve customer experience but also directly impacts productivity and operational costs, becoming a driver of profitability for retailers. Lastly, adapting to digital trends is a strategic component of the transition to biometric payments. In an increasingly technology-centric world, consumers seek shopping experiences that align with their digital lifestyles. The adoption of biometric systems does not only meet this demand but also positions retailers as proactive and adaptive leaders in the digital era, fostering a positive image and attracting a broader audience.

Understanding the factors that influence the intention to use any technology is crucial for optimizing investments and ensuring the delivery of value to customers by various stakeholders. Many research efforts have attempted to model technology adoption based on models derived from social psychology (Irimia-Diéguez et al., 2023). In this regard, the majority of academic research has focused on technical analyses of biometric systems themselves (Alfatni et al., 2023), or on behavioral modeling based on classical theories (Lee and Pan, 2023; Shiau et al., 2023).

This work focuses on Biometric payments cards (BPC) and its acceptance by retail users. Consequently, the objective of this work is twofold. Firstly, to identify the variables that predict the intention to use BPC using different feature selection methods from the area of Artificial Intelligence (AI). These methods will allow us to establish an importance ranking on the variables that participate in the decision-making process based on an online survey involving 1905 users with experience in mobile payment systems. Secondly, to contrast these results with a group of experts associated with the Fintech sector to determine the most relevant variables in the adoption process of BPC. The novelty of this research lies in the application of a mixed methodology involving both consumers and experts in the area. On the one hand, we analyze the importance of a set of variables by extending the UTAUT2 model through an online questionnaire developed over a significant set of consumers and subsequently modeling it using several algorithms. This approach allows us to establish different rankings according to each proposed technique (Study 1). These results are then tested by a group of 20 experts which evaluate each of the obtained rankings. This contrasting methodology has been employed in other studies, emphasizing its utility as the research findings combine the assessments of end-users and the evaluations of experts who define products and, to some extent, establish strategies for the creation and marketing of these innovations (Higueras-Castillo et al., 2023b; Guillén Perales et al., 2024).

Therefore, the proposed research is relevant by introducing a dual behavioral perspective using different metrics from primary data obtained through an online survey, and expert opinions from a group of professionals in the Fintech sector. The following Research Questions (RQ) are proposed for this purpose:

- **RQ1**: What are the key factors for the acceptance of biometric payments cards (BPC) by consumers?
- **RQ2**: Is there any consensus in determining these factors based on the type of metric employed?
- **RQ3**: Do the opinion of financial experts aligns with the results obtained from different metrics used?

To address the RQ posed, we propose the application of a hybrid research model that incorporates both quantitative and qualitative research methods. Notice that using a single method (either qualitative or quantitative) might be insufficient to describe the complex decision-making behavior in the adoption of the proposed technology (Venkatesh et al., 2016; Tu, 2018). For the first phase, Study 1, we define a holistic model incorporating the UTAUT2, the General Risk Theory, and the Trust Theory; all of them are theories related to the adoption of financial technologies (Kalinic et al., 2019; Belanche et al., 2022; Migliore et al., 2022). We evaluate the quantitative results using several statistical techniques to determine the significance of variables concerning the adoption of BPC. In the second phase, Study 2, we conduct in-depth interviews with a group of experts in the Fintech sector (Deshpande, 1983) to assess and explain the previously achieved results (Creswell et al., 2003).

The rest of this work is organized as follows. In Section 2, the key terms used in this investigation are defined, summarizing the importance of BPC, and describing the theoretical framework. Section 3 describes the formal methodology for data collection, the design of the survey, and the metrics employed in the definition of the problem. Finally, Sections 4 and 6 present the results of the analysis and the discussion, along with implications, limitations, and future lines of research, respectively.

2. Literature review

2.1. Biometric payments cards

BPCs combine chip technology with customers' fingerprints on a bank card to conveniently and securely verify the cardholder's identity for transactions. To this end, an integrated sensor, working within the chip, verifies the identity through a fingerprint. During a purchase, the integrated sensor captures and compares the cardholder's fingerprint with the digital one saved on the card. The cardholder's biometric data never leaves the card, as the extraction and verification of biometric data entirely occur on it. If the match is successful, the transaction is authenticated, and there is no need for the cardholder to provide a PIN or a signature (Mastercard, 2023).

One of the most relevant functionalities of biometric identification is related to the Directive PSD2 (Payment Services Directive). PSD2 is a regulation for electronic payment systems introduced in 2015 by the European Union. Its goal is to enhance the security, the efficiency, and the interoperability of electronic payment systems across Europe. This regulation requires that providers of payment services implement strict security measures, such as two-factor authentication, to protect customers' information and prevent fraud through: 1) something that only the user knows (password or security PIN); (2) something that the customer has (validation through the acceptance of a code communicated to the user's cell phone); and (3) something inherent to the user himself (iris or fingerprint).

Despite the benefits of this type of payment system, biometric technology can also pose some risks related to the collection and storage of biometric data, given the possibility of theft and fraudulent use. Unlike a password or a PIN code in other traditional payment systems, these data cannot be modified. Other concerns are about illegal use for surveillance and tracking purposes, potentially infringing on individual privacy and civil liberties. Additionally, there is the possibility of technical errors to recognize the person when the system fails, avoiding them to access to the payment services (Originstamp, 2023).

2.2. UTAUT model, Risk Theory and Trust Theory

The scientific literature has developed various behavioral decision theories and intention models to examine individuals' responses to innovations, many of which are based on research in social psychology (Pavlou, 2002). In the context of consumer behavior on the Internet, the literature review focuses on models and theories supported by specific marketing and information technologies studies. Specifically, the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), the Technology Acceptance Model (TAM) (Davis et al., 1989), and the Theory of Planned Behavior (TPB) (Ajzen, 1991) are highlighted in the scientific literature.

After extensively reviewing eight predominant technology adoption models, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), emphasizing the importance of analyzing utilitarian value (extrinsic motivation). Later, with the rise of consumer technologies, there was a need to extend the UTAUT model to the consumer context, emphasizing the hedonic value (intrinsic motivation) of technology users. This led to the incorporation of three new constructs, namely hedonic motivation, price value, and habit, into the original UTAUT, resulting in the popularly known and extended version called UTAUT2 (Tamilmani et al., 2021).

The UTAUT2 model has been extensively analyzed in the scientific literature, and it is considered by several authors as the best model for studying technology adoption (Higueras-Castillo et al., 2023a). In this line, it has been employed in several research studies related to payment systems (Al-Okaily et al., 2023). Table 1 defines the variables that are part of the UTAUT2 model.

All the proposed variables included in the UTAUT2 model are related to the object of the research: *Effort Expectancy* allows assessing the ease of use of BPCs and their improvement in usage; *Facilitation Conditions* will enhance the use of BPCs if adequate support services and resources are available; *Habit*, through the use of these payment systems, will improve the usage of BPCs; *Hedonic Motivation* ensures BPC usage if users find the technology attractive and enjoyable for their secure payment experience; *Performance Expectancy* will enhance the use of BPCs as long as this technology provides the expected benefits with its use; and finally, *Social Influence* will also have a positive effect on the intention to use BPCs when individuals close to them offer positive opinions and experiences.

Meanwhile, the inclusion of two additional theories is proposed to model the intention to use biometric payment systems: Risk Theory and Trust Theory.

Bauer (1960) suggested that a significant portion of consumer purchasing behavior may involve a certain risk because purchasing decisions could have unpredictable or unfavorable consequences (Yang et al., 2015). Numerous studies have demonstrated the influence of perceived risk in several adoptions of innovations linked to the financial sector, considering it a determining factor in their adoption, that significantly conditions the decision to use new technology (Liébana-Cabanillas et al., 2022a; Ramtiyal et al., 2023; Irimia-Diéguez et al., 2023; Bhatia et al., 2023; Pei et al., 2024). From our perspective, and in line with the proposals of Eksteen and Humbani (2021), the Theory of Perceived Risk is appropriate for this study for two reasons. First, given the lack of familiarity with biometric payments, consumers are likely to adopt a negative attitude toward them, making their adoption challenging. And second, because the adoption of innovative services is more influenced by perceived losses than perceived gains.

Moreover, in virtual environments trust is a difficult concept to explain due to its complexity, leading some authors to interpret it through credibility or security (Wang and Emurian, 2005). Traditionally, trust has been constituted by two basic components: cognitive and behavioral. From a cognitive perspective, Dwyer et al. (1987) defined it as the belief that the word or promise of one party is reliable, and that it will fulfill its obligations in a relational exchange. On the other hand, from a behavioral perspective, it is defined as the willingness of one party to be vulnerable to the actions of the other party, based on the hope that the other will perform a particular action important to the one who trusts, regardless of the ability to monitor or control the other (Mayer et al., 1995). In other words, it is the willingness or desire to follow a particular pattern of behavior. Consequently, this variable will determine the success of adoption, especially in innovations related to the financial sector (Chakraborty et al., 2022; Ramos de Luna et al., 2023a; Franque et al., 2023).

The use of different theories to analyze the usage intention of technologies related to Fintech is common in the field of social sciences (Wu and Liu, 2023). As previously discussed, the UTAUT2 model is one of the most widely used theories to define the usage intention of a technology, but it is equally true that this theory is enhanced by the inclusion of other variables, resulting in an extension of the model (Kuriakose and Nagasubramaniyan, 2024; Jafri et al., 2024). Table 2 summarizes some of the most recent research where the variables proposed in our investigation have been employed. The final proposed model is summarized in Fig. 1.

3. Methodological approach

3.1. Problem definition

This research proposes the implementation of a mixed-methods research approach, combining quantitative and qualitative research to synthesize findings (Venkatesh et al., 2003). The use of such mixed-methods research combines the design advantages of qualitative and quantitative research and is able to comprehensively and rationally explain various phenomena, achieving richer and more robust conclusions than single methods (Venkatesh et al., 2016).

The data for this research were acquired using a non-probabilistic sampling method with quotas, structured in accordance with the population demographics. *Toluna*, a specialized research company in sampling services, was engaged for the development of the questionnaire, wherein participants were assigned randomly. The collection of data was executed through an online survey employing a structured and precoded questionnaire designed on the *Toluna Quick Surveys* platform. To minimize participant attrition, the research's purpose was clearly communicated, and assurances of participant anonymity, data protection, and non-utilization of the data for other purposes were provided. The data collection phase started in January 2023 and concluded in March 2023.

Prior to the formal survey launch, a preliminary test was conducted

Table 1
Variables of the UTAUT2 model. Source: Venkatesh et al. (2012).

Effort expectancy	Degree of ease associated with consumers' use of technology
Facilitation condition	Refer to consumers' perceptions of the resources and support available to perform a behaviour
Habit	The extent to which people tend to perform behaviors automatically because of learning
Hedonic motivation	The fun or pleasure derived from using a technology
Performance expectancy	Degree to which using a technology will provide benefits to consumers in performing certain activities
Social influence	Extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology

Table 2
Related works using extensions of the UTAUT2 model. PT and PR stand for perceived trust and perceived risk, respectively.

Authors	Technology	UTAUT2	PT	PR
de Blanes Sebastián et al. (2023)	P2P payment	✓	✓	✓
Wu and Liu (2023)	Mobile payment	✓		✓
Namahoot and Jantasri (2023)	Mobile payment	✓		✓
Nandru et al. (2023)	Mobile payment	✓	✓	
Martinez and McAndrews (2023)	Mobile payment	✓		✓
Al-Okaily et al. (2024)	Mobile payment	✓	✓	
Kaur and Arora (2023)	Online banking	✓	✓	✓
Liebana-Cabanillas et al. (2024)	Biometric payment	✓		✓

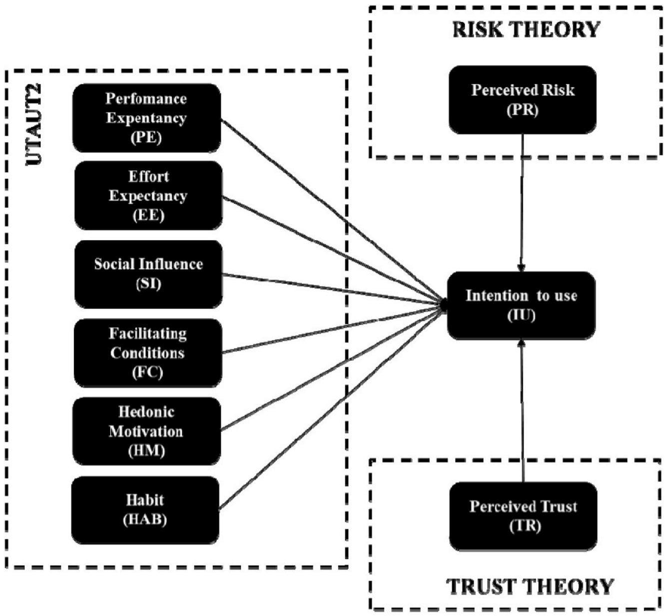

Fig. 1. Research model.

involving 5 experts and 50 participants to ensure questionnaire comprehension and alignment with research objectives. Following this initial phase, a pre-test was implemented to validate the scales defined in the earlier stage. This step focused on assessing and refining the questionnaire to gauge its acceptance, as well as the dimensionality, reliability, and validity of the proposed scales. Subsequently, once the scales were confirmed, the actual data collection ensued.

The final sample utilized in the analysis comprised 1905 users experienced in mobile payment systems. Examination of respondents' profiles revealed a higher representation of women (66.6%) compared to men (33.3%) in the sample. The average age of respondents was 31.7 years. Regarding educational attainment, a majority had completed university studies (41.90%), and the median income level fell between 1201 and 1500 euros (47.61%).

The demographic profile of the obtained sample aligns with the findings of the "II Study on Mobile Payment Trends in Spain," conducted by Visa Spain and Pecunvayo in 2022 (VISA and Pecunvayo, 2022). This congruence reinforces the representativeness of our sample, indicating that our research captures a demographic composition consistent with broader trends identified in a reputable study within the same geographical context and subject domain.

After the data collection, six methods were employed to characterize the intention of use of BPC, five of them based of defining a ranking on the different variables using feature selection methods from the area of AI (see Section 4.1) and one associated to a structural equation model (see Section 4.2). The results of this quantitative analysis were assessed by 20 experts in the Fintech industry, who evaluated the previous findings. After completing this initial study, ten in-depth interviews were conducted to assess the obtained results.

3.2. Development of the measurement scales

The proposed variables for the analysis were assessed using reflective measurement scales that had been validated in previous research and adapted to the context of the proposed payment system. All variables in the UTAUT2 model were measured according to the foundation set by Venkatesh et al. (2012). Regarding the measurement of the perceived risk, the scale from Singh et al. (2021) was adapted, while the adapted scale from Liébana-Cabanillas et al. (2020) was used to assess the perceived trust. All variables were evaluated on a 7-point Likert scale, where a score of 1 corresponded to "totally disagree", and a score of 7 to "totally agree". Since the original scales were in English, translations into Spanish were performed by a native translator to ensure the accuracy of the content. The scales used are detailed in Appendix A.

To verify the reliability and validity of the scales, we first checked the internal consistency using the Cronbach's alpha and the Rho coefficient. The values of both tests were above the recommended minimum threshold of 0.7. Additionally, all composite reliability (CR) values were above 0.90. Finally, as shown in Table 3, all values of the average variance extracted (AVE) were above 0.50 (Hair et al., 2019).

4. Methods

4.1. Methods based on feature selection

AI technologies, and more precisely Machine Learning (ML) techniques, provide a powerful tool to extract unknown, useful patterns from data (Abu-Mostafa et al., 2012), and has become state-of-the-art nowadays. Feature Selection (FS) (Li et al., 2017) is the AI problem of selecting a subset of features for an input data, preserving the same capability of discovering knowledge from it. It is usually performed in a preprocessing step, i.e. before designing the ML model. It is done in order to face the curse of dimensionality of ML techniques, which may cause overfitting, i.e., performance degradation on unseen data (Hastie et al., 2009) due the presence of redundant or irrelevant features in the data sample associated to the ML task to be solved. In our scenario, we use FS techniques to rank a set of input variables related to our analysis task.

The problem at hand is formally stated as follows. Let $D = \{(\{x_i^j\}^K, y_i)\}^N$ be a dataset of N input/output pairs (with $1 \leq i \leq N$), where $\{x_i^j\}^K$ is a set of K prediction features (with $1 \leq j \leq K$), and y_i is a target feature.[1] FS consists of finding a subset of features $\{x_i^j\}^{K'} \subseteq \{x_i^j\}^K$ with $K' \leq K$, preserving the learning capability of D.

FS techniques are usually classified into *filter* and *wrapper* methods (Li et al., 2017). Filter methods (Guillén et al., 2008) perform FS in an earlier step to training the ML model, whereas wrapper methods (Guillén et al., 2009) are integrated into the ML model, and are thus dependent of it. In general, filter methods are faster, cheaper, and more independent of the selected ML model. Therefore, this is the kind of techniques that we will use in our analysis.

Backwards Elimination (BE) (Guyon and Elisseeff, 2003) a very well-known filter method for FS. Essentially, it starts from the whole set of available features and iteratively selects at each step a single feature

Table 3
Composite reliability and validity. BI: behavioral intention; EE: effort expectancy; FC: facilitation condition; HAB: habit; HM: hedonic motivation; PEE: performance expectancy; PRISK: perceived risk; SI: social influence; TRUST: trust.

	Cronb. alpha	rho_A	CR	AVE
BI	0.951	0.951	0.965	0.872
EE	0.940	0.942	0.957	0.848
FC	0.924	0.929	0.946	0.815
HAB	0.911	0.912	0.944	0.849
HM	0.950	0.950	0.964	0.870
PEE	0.916	0.937	0.938	0.753
PRISK	0.923	0.975	0.944	0.808
SI	0.973	0.973	0.983	0.950
TRUST	0.971	0.971	0.978	0.897

[1] Without loss of generality, for simplicity we assume a single target feature y_i, but it can be also extended to a vector of target features $\{y_i^t\}^T$ with T values, if necessary.

that optimizes a given metric to be removed until the best performing feature subset is obtained. Hence, the features selected in the first rounds are considered as less relevant and more redundant with respect to the remainder for the ML task. Algorithm 1 describes the pseudocode of this technique, which receives the dataset D, a stop criteria, and a metric to optimize (maximize or minimize) as inputs.

Algorithm 1. Backwards Elimination (BE)

```
1: procedure BE(dataset, stopCriteria, metric)
2:     Prediction features P ← features(dataset)
3:     Target features y ← target(dataset)
4:     while not stopCriteria do
5:         f ← Feature from P optimizing metric
6:         P ← remove f from P
7:     end while
8:     D ← set of N pairs (P_i, y_i), with 1 ≤ i ≤ N
9:     return D
10: end procedure
```

In our case, since we are interested in obtaining a ranking of the whole set of available features according to their importance, the stop criteria is precisely that all the features have been selected, i.e., that the number of iterations in the *while* loop is exactly the number of input prediction features K. In particular, our ranking of features is constructed using the order of features selected in Alg. 1 Line ? Moreover, we must note that the ranking can be computed in both ascending and descending order, depending on the metric to optimize. For instance, the optimal value of a metric returning the worst (respectively best) feature with respect to those maintained (resp. incorporated) until now allows us to apply BE to build the feature ranking in ascending (resp. descending) order.

In the literature, there are many metrics used to perform FS. In our study, we focus on three very well-known and common metrics: mutual information, delta test, and fuzzy rough sets, which will thus compose alternative ways to define the feature ranking in our problem.

4.1.1. Mutual information

The Mutual Information (MI) (MacKay, 2003) estimates the amount of information that a variable X has about another variable Y. Its definition is:

$$MI(X,Y) = \int \frac{\mu_{X,Y}(x,y)\log(\mu_{X,Y}(x,y))}{\mu_X(x)\mu_Y(y)))}dxdy \tag{1}$$

where μ is the (joint) marginal density function. In the discrete case, this MI value can be approximated using histograms or bins (Kraskov et al., 2004).

In our work, we compute the MI-based loss using the concept of *Markov blanket* (Koller and Sahami, 1996). In particular, given a set of features $X = \{x^1, \ldots, x^K\}$, the Markov blanket of each feature $x^i \in X$ is the feature $x^j \in X$ maximizing $MI(x^i, x^j)$ (with $i \neq j$). Using it, the loss L of a feature x^i is computed as:

$$L(x^i) = MI(\{x^i \cup x^j\}, y) - MI(x^i, y) \tag{2}$$

where x^j is the Markov blanket of variable x^i, and y is the target feature of the dataset.

In the BE algorithm, the loss L is a metric to minimize. Therefore, at each step, the feature x^i with the lowest loss of information $L(x^i)$ is eliminated. In other words, x^i represents the variable that contributes the lowest to explain the target variable y. In consequence, the ranking is constructed in ascending order.

4.1.2. Delta test

Delta test (DT) (Eirola et al., 2008) estimates the noise between a pair of variables, and hence, it is a suitable metric to perform FS in the BE algorithm. For a given dataset $D = \{(\{x_i^j\}^K, y_i)\}^N$, DT is defined as:

$$DT_{N,t} = \frac{1}{2N}\sum_{i=1}^{N}(y_i - y_{nn[i,t]})^2 \tag{3}$$

where $nn[i, t]$ is the t-th nearest neighbor to $\{x_i\}$.

Although there are several metrics to measure the distance between two vectors, the most common one is the Euclidean distance (the one we use). Moreover, when $t = 1$, $DT_{N,1}$ becomes the variance of the noise in the target feature y, thus it represents an estimation of the minimum mean squared error that can be obtained by a ML model without overfitting in a regression problem.

In the BE algorithm, DT is a metric to maximize, and, therefore, the ranking of features is constructed in descending order.

4.1.3. Fuzzy rough sets

Rough set theory (Yang and Yang, 2012) determines lower and upper approximations of a concept based on object indiscernibility, i.e., objects that certainly or possibly belong to a given concept, respectively. Fuzzy rough sets (Yeung et al., 2005) extend this theory by allowing the approximation operators to be fuzzy.

The fuzzy lower approximation of a concept can be defined as:

$$(R\downarrow A)(y) = \inf_{x \in X}(\mathscr{I}(R(x,y), A(x))) \tag{4}$$

where R is a fuzzy relation in X, A is a fuzzy set, $\mathscr{I}$ is a fuzzy implication, and $y \in X$. Using this approximation, the positive region is defined as the union of the lower approximations of the decision classes in X.

Fuzzy Rough Feature Selection (FRFS) (Cornelis et al., 2010; Jensen and Shen, 2009) consists of selecting the set of features that maximizes the positive region of X, until matching the size of the positive region considering all features, or until a given number of features is selected. Fuzzy rough sets have become a very powerful AI tool for the FS task as they allow us to measure the importance of each individual feature in an environment affected by imprecision and uncertainty, which is inherent to many real-world applications (Ji et al., 2021).

In order to integrate FRFS in the BE algorithm, we set the number of selected features to 1, and remove the selected feature from the input dataset D at each step. This way, the ranking of features is constructed in descending order.

4.1.4. Aggregation of individual feature rankings

In order to get an aggregated ranking using the individual rankings provided by each of the latter metrics, we perform a positional voting system with the original Borda count (Saari, 2003). This is, each individual ranking gives 1 point to the variable in the last position, 2 points to the variable in the second-to-last position, etc. Then, for each variable, these points are summed up, and variables are finally ranked according to the aggregated scores.

Notice that this aggregated ranking can be computed for any combination of the available rankings, i.e., either using the three individual rankings obtained with the previous three metrics, or just using a subset of them.

4.2. Structural equation modeling

The last technique involves the modeling of structural equations (SE) using the Partial Least Squares (PLS) method through the SmartPLS software (Ringle et al., 2015). Relationships were tested through the comparative analysis of structural coefficients, and bootstrapping analysis was conducted with 5000 randomly selected subsamples from the original dataset (Hair et al., 2019).

In this case, all the relations were found to be significant ($p < 0.05$), except for the relationship between social influence (SI) and intention to use (BI).

5. Results

5.1. Study 1: application of quantitative methods

Table 4 summarizes the order of importance for the variables according to the results provided by each of the considered techniques. The first interesting conclusion to be drawn is that the ranking provided by each individual method (rankings 1, 2, 3, and 5) show a large disparity. We can observe some extreme cases such as the fact that the variable considered as the most and the second most important in rankings 3 (FRFS method) and 1 (MI-based FS method) is the least important for method 5 (SE), while the most important in ranking 5 is the second least important in ranking 1. Hence, we can clearly conclude that the approach (FS or SE) and the metric considered within the FS approach have a strong influence on the results.

To validate the experimental results, a group of 20 experts in the Fintech field was consulted, each having a minimum of 10 years of experience in the sector. These experts were selected from five financial entities with presence in Spain. The interviews conducted within the framework of this study were designed following a semi-structured methodology (Yin and Chun, 2024). This approach was carefully chosen to allow the collection of both quantitative and qualitative data. In semi-structured interviews, experts were provided with an initial set of open-ended questions, thus enabling a thorough exploration of their experiences and perceptions. Additionally, they were given the freedom to express additional ideas they considered relevant to the topic under discussion, enhancing flexibility and uncovering aspects that were not considered previously (Mayer, 2004). During the investigation, initial generic questions were posed to allow the researchers to thoroughly explore the phenomenon under study. As the interviews progressed, follow-up questions based on participants' significant comments about the technology were incorporated (Acun and Yilmazer, 2019). All interviews were recorded and transcribed comprehensively. Data collection spanned several weeks based on the work availability of each participating expert, and it concluded when the theoretical saturation was reached, i.e., when the data no longer contributed new insights. This flexible and in-depth approach in interviews allowed for a richer and more detailed understanding of participants' experiences and perspectives. Additionally, the generation of new knowledge during the interview process contributed to the enrichment of the research (Acun and Yilmazer, 2018). This type of interview has been previously employed to explore new technologies related to Fintech (Tang et al., 2021; Li et al., 2023).

The validation process was divided into two stages: interviews and evaluation of the proposed methods. In the first stage, the methods were explained to the experts to determine the subset of variables considered relevant for the intention to use BPC. Next, the results of the methods (i.e. the order of importance of the variables provided by each of them) were presented to the experts and they were asked to rated them using a Likert scale (1–7). Table 5 summarizes the scores that each expert assigned to each of the proposed methods.

Overall, the experts' scores revealed that the most highly valued criterion was MI (ranking 1, with an aggregated Likert value of 6.1), aligning with the results of previous research (Liébana-Cabanillas et al., 2016). In second place, ranking 4b, based on the aggregation of two FS methods, MI and FRFS (i.e., based on the aggregation of rankings 1 and 3), received the second-highest evaluation. However, it is noteworthy that this aggregation (with a score 5.9) does not improve one of the two individual methods considered, solely based on MI (with a score 6.1). The third-highest-rated method is 4a, aiming to aggregate the three feature selection methods based on an individual metric (rankings 1 to 3), demonstrating once again how the aggregated rankings are consistently dominated by the strong performance of the MI-based feature ranking. Finally, the least valued methods are the one based on DT (ranking 2) and the one based on structural equation systems (ranking 6).

We should note that the experts' evaluations have been actually obtained by means of a two-round procedure. In the first one, the experts were only provided with five different feature rankings to evaluate: the three corresponding to the individual feature selection metrics (MI, DT, and FRFS, i.e. rankings 1 to 3), the ranking resulting from the aggregation of these three proposals (ranking 4a), and the ranking resulting from the SE model (ranking 5). From the experts' opinions for these five rankings, we could recognize that ranking 2 (DT) was evaluated as a very bad solution, with an aggregated Likert value almost as bad as the worst one, the SE approach (1.7 vs 1.1). As a consequence, we thought that it did not make sense to consider the DT-based ranking for the aggregation and designed a new feature ranking (ranking 4b) based on aggregating only the MI- and FRFS-based rankings (rankings 1 and 3, respectively), both of which had obtained a good evaluation from the requested experts. We did not consider the SE ranking (ranking 5) for any aggregation as it showed the worst performance of all the methods considered.

5.2. Study 2: personal interviews

Once the evaluation stage of each proposed method was completed, ten in-depth interviews were conducted to assess the obtained results. The interviewees confirmed the importance of the method providing

Table 4
Summary of results. MI: Mutual information-based ranking, DT: Delta test-based ranking; FRFS: Fuzzy Rough Feature Selection-based ranking, Agreg-A: MI-DT-FRFS aggregation-based ranking, Agreg-B: MI-FRFS aggregation-based ranking, SE: Structural equation model-based ranking. EE: effort expectancy; FC: facilitation condition; HAB: habit; HM: hedonic motivation; PEE: performance expectancy; PRISK: perceived risk; SI: social influence; TRUST: trust. (*): not significance.

Rank 1 (MI)	Rank 2 (DT)	Rank 3 (FRFS)	Rank 4a (Aggr-A)	Rank 4b (Aggr-B)	Rank 5 (SE)
PRISK	EE	SI	SI	SI	EE
SI	FC	PEE	FC	PRISK	PEE
FC	TRUST	EE	EE	PEE	FC
HM	HAB	PRISK	PRISK	FC	HM
TRUST	PEE	FC	PEE	EE	TRUST
PEE	HM	HM	TRUST	HM	HAB
EE	SI	HAB	HM	TRUST	PRISK
HAB	PRISK	TRUST	HAB	HAB	SI(*)

Table 5
Experts' scores to the results of each ranking method.

	Rank 1 (MI)	Rank 2 (DT)	Rank 3 (FRFS)	Rank 4a (Aggr-A)	Rank 4b (Aggr-B)	Rank 5 (SE)
Expert 1	7	1	3	3	6	1
Expert 2	7	2	2	4	6	1
Expert 3	6	2	2	3	5	1
Expert 4	6	2	4	4	5	2
Expert 5	6	2	3	3	5	1
Expert 6	6	1	3	4	6	1
Expert 7	5	2	5	3	6	1
Expert 8	5	2	3	3	7	1
Expert 9	6	2	4	4	7	1
Expert 10	7	1	5	5	6	1
Expert 11	6	1	3	4	6	1
Expert 12	5	2	5	3	6	1
Expert 13	5	2	3	3	7	1
Expert 14	6	2	4	4	7	1
Expert 15	7	1	5	5	6	1
Expert 16	6	2	5	4	6	2
Expert 17	6	1	4	5	7	1
Expert 18	6	2	5	4	6	2
Expert 19	6	2	5	3	6	2
Expert 20	7	1	3	4	6	1
Average	**6**,15	**1**,60	**3**,45	**3**,50	**5**,75	**1**,30

ranking 1 (MI-based FS) due to the higher significance they attributed to the risk (first variable in the ranking) and trust (ranked in fifth position), unlike the other methods that assigned a lower position in the ranking to these variables.

The respondents emphasized this importance as, in their view, "*risk is a very important variable in the adoption of payment systems; it was significant in the past with credit cards and later with mobile phone payments*".

On the other hand, "*trust can also determine whether a user is willing to try a banking technology that provides a greater security and protects their account balance*". This reflection is repeated in other statements, reflecting the high level of fraud occurring in some payments: "*customers are increasingly cautious when deciding to use new payment systems*".

It is very interesting that, despite the differences in the positions of the methods that obtained a high score regarding the variables trust and risk, both variables capture a significant portion of the respondents' comments. This indicates that, even though these two variables are conceptually different, they are intrinsically related.

Asked about the second variable, social influence, all the experts also agreed, stating that "*currently, the influence of people close to users often determines an initial approach to a technology. This situation is more common in younger people who quickly change their intentions simply because a friend has mentioned something or they have seen a shared content about it on a social network*".

In light of these initial reflections, the effect of the number of years of experience of the 20 experts who evaluated the proposed methods was analyzed. In this case, the results of the two highest-rated methods are inverse. When dividing the sample of experts based on the average number of years of experience (an average of 17 years of experience for the total sample), it is observed that for those experts with more seniority (experience), the most valued variable in defining adoption is the perceived risk. In contrast, those experts with less experience believe that social influence is more determinant than risk in adopting BPC (see Fig. 2). This result aligns with the proposals of Al-Okaily et al. (2020) and García de Blanes Sebastián et al. (2023), emphasizing the importance of the opinions of people close to users when deciding to use a novel technology, even above other variables that might be considered decisive *a priori*.

Finally, the experts also agreed that habit in such innovative technologies can hardly influence their intention to use, as "*any technology that is so novel is not questionable for potential users, and instead, they will define this intention based on other variables such as risk, utility, or even facilitating conditions*".

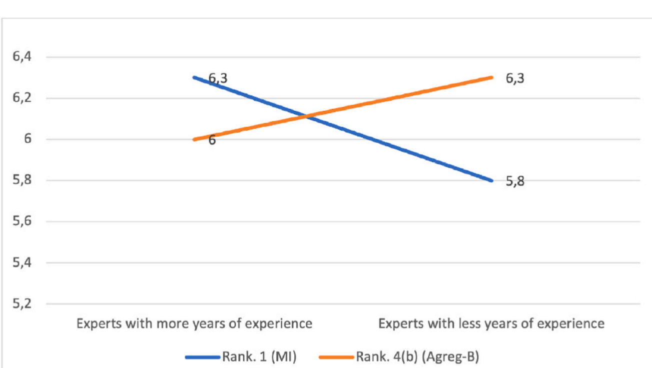

Fig. 2. Average analysis from methods based on rankings 1 (MI) and 4b (Aggr-B).

6. Conclusions, implications, limitations, and future research directions

6.1. Discussion

In the last few years, the changes in the financial and commercial landscape have been rapid and technology-driven. Innovation has given rise to new payment options that are reshaping the concept of money and the patterns of value exchange among users (Park et al., 2019). The trend towards process automation and the growth of online commerce have also influenced the transformation of payment methods. In this scenario, biometrics emerges as one of the novelties in payment modalities, emphasizing its user-friendly nature (Zhong et al., 2018).

Despite its current use, biometrics has not yet reached its full potential, and it is highly likely to continue improving in the realm of payment methods (Moriuchi, 2021). Consequently, the adoption of contactless payments with biometric technology will continue to grow in the retail sector (Burt, 2021). In the biometric payment methods currently in use, fingerprint scanning and facial recognition through the user's device stand out. The future is moving towards facial, oral, and ocular recognition. In addition to validating payments through the face or voice, users will be able to carry their personal keys and passwords through visual identification (Liébana-Cabanillas et al., 2022b).

The true innovation will focus on the popularization of systems based on biometric points of sale, allowing the initiation and authentication of payments through the biometric recognition of individuals, eliminating the need for credit cards or mobile devices. This approach is already common in the United States and Asia, and it is expected that Europe will also adopt this trend.

Biometrics represents an innovative approach that offers significant advantages by eliminating the need for cards or mobile devices in payment methods, resulting in increased speed and convenience. Moreover, it enables payments at any time, eliminating the need to remember passwords and fostering greater confidence in user identification (Shiau et al., 2023).

The shift towards biometric payments in the retail sector signifies a strategic leap in the direction of modernization and enhancement of customer experience. The amalgamation of heightened security, operational efficiency, and alignment with digital trends renders this approach not merely valuable but indispensable in an increasingly competitive market. The investment in biometric payments does not only serve the interests of consumers and retailers but also propels the ongoing evolution of the retail industry in the digital era.

6.2. Theoretical implications

Our research initially aimed to analyze the key factors for the adoption of BPC, proposing several methods that yielded different results, with diverse rankings based on the methodology employed. To discern these potential differences, a group of 20 experts was engaged to evaluate each of the outcomes, consistently highlighting the metric most valued, which was MI-based FS (ranking 1), aligning with findings from prior research (Liébana-Cabanillas et al., 2016). Ultimately, these results were shared and discussed with another group of 5 experts who assessed the obtained outcomes.

This contrasting methodology, in which a double analysis has been used, favors the results obtained and includes the professionals' own experience in decision making or in the recommendation itself (Chinchanachokchai et al., 2011), as well as the retail users' own opinions (Plotkina and Munzel, 2016). The majority of experts in this latter phase emphasized the importance of both risk and trust as interrelated factors, as well as social influence, characteristic of technological innovations.

The differences obtained according to the experience of the 20 experts who evaluated the ranking results are noteworthy. In this case, it is observed that experts with more experience focus their assessment on variables such as risk, unlike younger experts who give more weight to the influence of third parties when determining the proposed innovation. This result reinforces the perspective already proposed and corroborated by other authors, concluding the importance of considering the age of users in defining behavior (Kim and Ho, 2021). In this case, the variable of age (experience in the sector) is contrasted in the experts' own assessment of each of the proposed rankings.

This study also provides practical implications useful for improving the acceptance of BPC technology according to the opinions of expert groups that have evaluated the obtained rankings at the methodological level. Since risk and trust have been one of the most valued and questioned variables by both end-users and expert groups, providers of such services as well as the companies marketing them, if applicable, should work on enhancing user perception of risk and trust. The focus should be on how to reduce the perceived risks of this technology and how trust can be improved. Additionally, it is crucial to highlight the opinions of all users, reinforcing the positive message of its use through social influence from the stakeholder groups of potential users.

In summary, the obtained results provide the following answers to the Research Questions addressed in our study:

- **RQ1**: The key factors for the acceptance of BPCs by consumers are the perceived risk and the social influence.
- **RQ2**: There is a consensus among experts in determining these factors, being the MI-based FS (ranking 1) the most valued metrics, which aligns with previous studies.
- **RQ3**: In general, the opinion of financial experts aligns with the obtained results. However, depending on experience seniority, experts focus their assessments on either risk (experts with more experience) or social influence (experts with less experience).

6.3. Managerial implications

The constant evolution of the financial and commercial landscape, driven by unprecedented technological advancements, has caused a rapid reconfiguration in the last years. This transformation has been particularly notable in the field of payment systems, where innovation has given rise to a variety of new alternatives that are changing the way we conceive money and conduct financial transactions. While innovations like NFC or QR systems were initially groundbreaking (Ramos de Luna et al., 2023b), biometric payment systems have emerged as one of the most prominent and promising trends (Zhang and Zhang, 2024).

The adoption of biometric payments not only represents a change in the way we conduct transactions but also has a significant impact on the retailing sector and consumer services delivery. These systems provide a more secure, convenient, and efficient way of making payments, which can greatly enhance the customer experience and build trust in e-commerce and digital transactions. These elements are highly valued by users (Hwang et al., 2024).

This study offers a set of practical implications that are crucial for promoting greater acceptance and adoption of biometric payment technology. These implications derive from evaluations conducted by expert groups that have carefully analyzed the obtained rankings at a methodological level, ensuring their relevance and validity in the current context. Additionally, insights from the end-users who have expressed their intention to use the technology based on a set of proposed variables further contribute to these implications.

First, the close relationship between the acceptance of biometric payments and psychological and social factors such as risk perception, trust, and social influence is highlighted. Therefore, it is crucial for companies to develop marketing strategies that effectively communicate the security and reliability of biometric systems while proactively addressing consumer privacy concerns. Consumer education plays a fundamental role here, as informing users about the benefits and security of this technology can play a key role in stimulating its adoption.

Second, the importance of security in the acceptance of biometric payments is emphasized. Organizations offering such solutions must prioritize the development of secure and robust platforms, involving continuous investment in security measures and the adoption of advanced encryption and data protection technologies. Only through a proactive approach to security can gain and keep the users' trust about these systems.

Furthermore, the need for collaboration and continuous learning in a constantly evolving technological environment is emphasized. The Fintech industry is in a state of constant change, and companies wishing to stay at the forefront must establish strategic partnerships with experts and opinion leaders in this field. These collaborators can provide valuable insights into emerging trends, market expectations, and best practices in security and user experience. For this reason, the vision provided by experts in defining new payment systems will be vital for the intensive development of customer usage.

On the other hand, ease of use and user experience play a crucial role in the adoption of biometric technology. Therefore, companies should focus on designing intuitive interfaces and fluid and satisfactory user experiences that eliminate any friction in the payment process. Simplicity and convenience are crucial to fostering the adoption and retention of users in this domain.

In parallel, the importance of transparency and corporate responsibility in handling biometric data and user privacy is highlighted. Companies should review and adapt their business policies to ensure compliance with privacy and data protection regulations, and they must communicate their practices in this regard clearly and transparently. User trust is an invaluable asset in the digital economy, and only through responsible data management long-term loyalty and commitment can be ensured.

Finally, it is essential to highlight the role of artificial intelligence (AI). AI allows for the continuous improvement of the accuracy and efficiency of biometric systems by analyzing large volumes of biometric data and detecting patterns and anomalies more quickly and precisely than traditional methods. Moreover, AI technologies can be used to develop machine learning algorithms that dynamically adapt biometric systems to the individual preferences and behaviors of users, significantly enhancing the user experience and reducing the likelihood of errors (Wu et al., 2024). Additionally, AI methods can play a crucial role in fraud detection and prevention by identifying suspicious behaviors or attempts of identity fraud in real-time.

6.4. Limitations, recommendations, and future lines of research

Despite the significant results obtained in this study on the intention to use BPC, it is crucial to recognize some inherent limitations in the research and identify possible areas for future improvement that can contribute to the advancement of knowledge in this field.

Firstly, regarding the size and representativeness of the sample, although a significant sample of users with experience in mobile payment systems was used, it is essential to consider that none of them have experience with BPC. In subsequent research, it would be beneficial to expand the sample to include users who have used this technology occasionally, even conducting cross-cultural analyses to observe inferences by countries.

Secondly, concerning the theoretical framework used, although the UTAUT2 model provides a robust framework along with the General Risk Theory and the Trust Theory for analysis, there are other variables that could be included in the intention to use BPC and have not been considered. For example, the perception of convenience, the compatibility with other devices and systems, and the flow could be considered in future research to obtain a more holistic understanding of the factors influencing the adoption of these cards.

Additionally, although up to six different techniques have been used in this study to model the intention to use, each of them has its own limitations. With respect to the methods based on FS, we should notice that the three basic methods, considering the three initial metrics, showed significantly different results. Therefore, the approach is not robust with respect to the choice of the feature importance metric (see Section 4.1), and thus the most appropriate metric must be chosen for each specific study. In addition, although we expected that an aggregation of the results of more than one metric could outperform the best rankings provided the individual metrics, that has not been the case and the MI metric in isolation has resulted in a better feature ranking according to the experts' opinions. Future research could consider developing an aggregated index that allows jointly assessing the variables proposed as antecedents of the intention to use BPC. Moreover, different methodological approaches, such as case studies or controlled experiments, could be explored to strengthen the validity and generalizability of findings, or even including the analysis of methods based on neural networks.

Furthermore, it is crucial to highlight the potential limitation related to the temporal duration of the study. Since the research was conducted over a specific period, the results may reflect the conditions and perceptions of users at that particular time. However, the dynamics about the usage of technology can evolve over time due to changes in the technology itself, as well as because of changing attitudes and expectations of users. Future research could consider conducting longitudinal studies to capture trends and changes over time.

Finally, as BPC continue to evolve and become more widespread among users, it will be crucial to investigate and understand the impact of these cards on the industry and their regulation. This could include analyzing changes in payment processes, transaction security, interoperability with other systems, and legal and regulatory challenges.

CRediT authorship contribution statement

Carmen Zarco: Writing – original draft, Methodology, Conceptualization. **Jesús Giráldez-Cru:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Oscar Cordón:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Formal analysis, Conceptualization. **Francisco Liébana-Cabanillas:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Measurement scales used in the survey

Table A.6 reports the statements scales used in the survey.

Table A.6
Statements evaluated in the survey.

Acronym	Statement	Reference
PEE1	BPCs are of use to me in everyday life	Venkatesh et al. (2012)
PEE2	Using BPCs helps me carry out my transactions quickly	
PEE3	Using BPCs improves my productivity	
PEE4	Using BPCs increases my productivity	
PEE5	I believe BPCs will help me achieve things that are important to me	
EE1	It is easy to learn how to use BPCs	Venkatesh et al. (2012)
EE2	BPCs are clear and understandable to use	
EE3	Skills in using BPCs are easily acquired	
EE4	I find it easy to use BPCs	
SI1	People I consider important in my life think I should use BPCs	Venkatesh et al. (2012)
SI2	Most of the people whose opinions I value think I should use BPCs	
SI3	People close to me would agree that I should use BPCs to buy a product	
FC1	I have the necessary resources to use BPCs	Venkatesh et al. (2012)
FC2	I have the necessary knowledge to use BPCs	
FC3	I can get help from others when I have difficulties using BPCs	
FC4	BPCs are compatible with other applications I use	
HM1	Using BPCs can be fun	Venkatesh et al. (2012)
HM2	Using BPCs is fun	
HM3	I enjoy using BPCs applications	
HM4	Using BPCs is enjoyable	
HAB1	Using BPCs has become a habit to me	Venkatesh et al. (2012)
HAB2	I must use BPCs	
HAB3	Using BPCs has become natural to me	
BI1	Assuming I had access to BPCs, I would intend to use it to make my purchases	Venkatesh et al. (2012)
BI2	Assuming I had access to BPCs, I would use them in the next few months	
BI3	Assuming I had access to BPCs, I would intend to use them frequently	
BI4	I will always try to use BPCs in my payments	
PRISK1	Other people may uncover information about my online transactions if I use BPCs	Singh et al. (2021)
PRISK2	There is a high potential for monetary loss if I make my purchases using BPCs	
PRISK3	There is a significant risk in making my purchases using BPCs	
PRISK4	I consider making my purchases using BPCs to be a risky choice	
TRUST1	I trust that my personal information is safe in BPCs	Liébana-Cabanillas et al. (2020)
TRUST2	I trust that BPCs contains all my bank information accurately	
TRUST3	Over all the BPCs is trustworthy	
TRUST4	Over all the BPCs keeps my financial information secure	

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