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Can cluster analysis enrich the innovation resistance theory? The case of mobile payment usage in Italy

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ABSTRACT

Mobile payments provide several benefits, for consumers and merchants alike. Yet, on a worldwide scale their usage is still low. Also, the barriers to mobile payment usage are still a rather unexplored topic in the literature, which is instead focused on adoption behavior. Accordingly, our objective is to investigate the factors that hinder, respectively, mobile payment usage and intention to use by consumers. The theoretical framework for our analysis integrates the Technology Readiness Index (TRI) into the Innovation Resistance Theory (IRT). To empirically assess the model, we gathered data on mobile payment usage in Italy through a web-based survey among 1,795 consumers. For the full sample, we find that the impact of the IRT barriers is different for actual use and behavioral intention to use. Also, and most importantly, once we segment consumers based on their TRI, we find yet other results. Specifically, the impact of the IRT barriers is different across the proposed clusters. This confirms that cluster analysis does indeed add value to the IRT.

1. Introduction

Paying is one of the most important economic activities. It has changed dramatically over time, from barter to payment cards – and beyond [1]. The progress of information technology has enabled dramatic innovation in electronic payments, and adoption has continued to grow, thanks to their increased safety and convenience [2]. A recent trend that is receiving growing attention is mobile payments [3], defined by the European Central Bank (ECB) as payments *"where a mobile device is used at least for the initiation of the payment order and potentially also for the transfer of funds"*.[1]

Mobile payments provide several benefits, for both consumers and merchants, from increased convenience, security and speed, to reduced transaction costs and higher customer loyalty [4,5]. Nevertheless, their adoption by consumers is still low on a worldwide level [4,6]. Interestingly, according to a survey conducted by Statista Digital Market Insights, penetration at the Point of Sale (POS) is heterogeneous, with Asian countries showing higher usage: in 2023, in China 38.25 % of all transactions at the POS were paid for using a smartphone – the highest level of all countries – compared to only 19.62 % in the US and 17.17 % in the European Union (EU) [7].

Accordingly, the objective of the present paper is to investigate the barriers to the usage of mobile payments on the consumer side, analyzing both users and non-users. Several studies have already analyzed the adoption and usage of mobile payments in a range of countries, such as Finland, Germany, Indonesia, Japan, South Africa, South Korea, and the US [8–14]. More recently, Amoroso & Ackaradejruangsri [15] use a Dual Factor Model to analyze the drivers of the intention to use mobile payment apps in Japan, finding a positive impact of perceived value and enjoyment. Conversely, privacy and security concerns negatively affect adoption intention, through perceived risk. Dimitrova [16] analyzes the factors that influence the intention to "fully" adopt mobile payment in two groups of individuals in Sweden, namely users who want to continue using mobile payment (adopters-accepters, AA) and users who are hesitant to keep doing so (adopters-resisters, AR). Interestingly, the results are different across the two groups: the intention to fully adopt mobile payment among AR is driven by usefulness, social influence, and credibility, whereas the only significant driver of AA's intention is credibility. Shah Alam et al. [17], for their part, combine the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Stimulus-Organism-Response (SOR) model to analyze which factors increase the intention to continue using

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[1] https://www.ecb.europa.eu/services/glossary/html/glossm.en.html#598.

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QR code-enabled mobile payment in Bangladesh. They find the main drivers to be effort expectancy, performance expectancy, and trust in the service. Similarly, for the case of Saudi Arabia, Yamin & Abdalatif [18] find that the main drivers to continue using mobile payments activated through QR codes are perceived usefulness, perceived ease of use, convenience, social norms, and innovativeness.

Crucially, if one moves beyond individual studies and instead takes a helicopter perspective, a key observation emerges: as already reflected in the above brief discussion of recent papers, extant research mainly focuses on who adopts mobile payments and why. The problem with this is that identifying the barriers to adoption, and the reasons why consumers postpone or reject it, could also provide valuable insights for both practitioners and scholars, perhaps even more so [19–21]. Only few studies explicitly investigate consumer resistance towards mobile payments [22–24].

Another, broader reason to delve further into the matter can be found in Lee et al. [25]. Lee et al. argue that numerous empirical studies in behavioral Information Systems (IS) theory research fail to yield relevant knowledge because they confirmatively test self-evident axiomatic theories; that is, theories that are *"acceptable as self-evident truth without the need for further empirical testing"* ([25], p. 148). To examine the extent of the issue, the authors conducted a horizontal analysis of a broad range of IS theories. More specifically, they analyzed 666 hypotheses from 72 representative behavioral IS theories, such as the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the UTAUT. Lee et al. [25] find that more than 60 % of the hypotheses – some of which relate to mobile commerce or smart cards – could be classified as axiomatic. Finally, there is little academic research on the segmentation of users of mobile payment, even though it could be pivotal in increasing our understanding of this form of consumer behavior [14,26].

To address these gaps, our study first clusters consumers based on their score for the Technology Readiness Index (TRI), which reflects consumers' attitude towards technology in general [27]. Subsequently, we investigate the factors that hinder the use of mobile payments – and that, in some cases, can lead to rejection – by applying the Innovation Resistance Theory (IRT) [27,28], first for the full sample and subsequently for each of the clusters. In particular, we test the validity of the theory across the clusters to determine whether there are disconfirming boundary conditions; i.e., whether there are conditions under which the theory is no longer valid, as suggested by Lee et al. [25]. To the best of our knowledge, we are the first to combine TRI and IRT in this way. From a managerial point of view, the results of our segmentation of consumers could provide useful insights for digital payment providers and public institutions that wish to foster the usage of the technology.

The remainder of the paper is organized as follows. Section 2 sets the stage by describing the Italian payments landscape and underpinning its relevance for the issue at hand. Section 3 presents the theoretical framework and Section 4 explains the sampling and data collection. Results are presented and discussed in Sections 5 and 6, respectively. Section 7 presents the limitations and conclusions.

2. The Italian payments landscape

The Italian context serves as an interesting case to examine mobile payment usage. According to statistics published by the European Central Bank,[2] the infrastructure for the acceptance of electronic payments is well developed. As of 2023, at 55,306 per million inhabitants, the number of POS terminals was well above the EU average of 45,956. The number of payment cards per capita (1.75) was only slightly lower than the EU average (1.95). Nevertheless, actual usage of these cards in Italy is still low. In 2023, the number of card payments per capita per year amounted to 123, compared to 185 in the EU.

Similar observations can be made concerning mobile payments. In 2023, there were 46.05 million smartphone users in Italy, which amounts to a penetration rate of 78.2 % [29], similar to the European average of 78.9 % [30]. However, usage of such phones to make payments is still very low. In 2023, only 10.67 % of all transactions at the POS were paid for by means of a mobile device, substantially less than the 17.17 % in the EU overall [7].

Mobile payment in Italy mainly takes two forms: (1) digital wallets based on near-field communication (NFC) technology, and (2) digital wallets based on other technologies, such as geolocation or QR codes [31]. The first category includes wallets such as Apple Pay, Google Pay and Samsung Pay. It is by far the most used type: of the 15.5 billion euro that was transacted in store by means of mobile payment methods in 2022, 89 % was paid for by means of an NFC wallet [32]. The second category includes apps that allow users to make account-to-account payments, both in a business-to-consumer and in a peer-to-peer setting. The most popular is Satispay, with over 4 million users.[3]

The two types also differ in terms of acceptance by merchants. NFC wallets allow consumers to make transactions by bringing their smartphone near a contactless card reader. Thus, for a merchant to be able to accept this type of payment it is sufficient to have such a reader. Since 2014, it is mandatory for Italian merchants to accept card payments, meaning that they are required to have a card reader. According to data published by the Innovative Payments Observatory, in 2022 of the over 3 million active terminals, 90 % had the contactless function. Hence, the majority of Italian shops are able to accept NFC mobile payments. Conversely, mobile payment apps, such as Satispay, are closed systems, which require both the payer and the payee to be registered on the platform. Moreover, the acceptance of this type of electronic payment is not mandatory by law. The upshot is a dramatically lower penetration rate on the merchant side. Satispay, for instance, counts about 230,000 registered shops.[4]

Since mobile payment usage in Italy is still in its infancy, in our survey we were primarily interested in which consumers are willing to move on from the existing payment instruments – and why (not) – rather than which mobile payments technology they prefer. Hence, in the questionnaire we did not restrict non-users in their choice and simply defined "mobile payment" as the act of paying with a mobile phone – a definition that covers both of the two above types.

3. Theoretical framework

In this section we first present the TRI and the IRT. Subsequently we define the three forms of innovation adoption/resistance that we will examine: use, postponement, and rejection. In a fourth and final subsection, we introduce the research model, together with the hypotheses.

3.1. Technology Readiness Index (TRI)

We resorted to the TRI because it is important to take into account the technology readiness of consumers [14]. The mere existence of a new technology such as mobile payments does not necessarily imply that consumers are fully ready to adopt it [8]. An interesting feature of the TRI is that it is not a measure of competence or knowledge about a specific technology, but rather reflects a consumer's attitude towards technology in general [33]. This allows us to analyze and cluster both users and non-users of mobile payments, suiting the goals of the paper.

The first version of the TRI, also referred to as TRI 1.0, was a 36-item scale developed by Parasuraman in 2000 to measure *"people's propensity to embrace and use new technologies for accomplishing goals in home life and*

[2] https://data.ecb.europa.eu/data/data-categories#payment-statistics accessed on August 2nd, 2024.

[3] https://www.satispay.com/it-it/come-funziona/, accessed on July 29th, 2024.

[4] https://www.satispay.com/it-it/cashback/, accessed on July 29th, 2024.

at work" ([34], p. 308). Parasuraman & Colby [35] updated and simplified the TRI since, in the meantime, the technology landscape had experienced substantial changes with the introduction of, for example, high-speed Internet access, social media, and mobile commerce.

The TRI 2.0 is composed of four dimensions: optimism, innovativeness, discomfort, and insecurity. Optimism is defined as *"a positive view of technology and a belief that it offers people increased control, flexibility, and efficiency in their lives"* (o.c., p. 60). Innovativeness is *"a tendency to be a technology pioneer and thought leader"* (ibid.). Both optimism and innovativeness are considered motivators; i.e., factors that drive technology readiness. Discomfort is described as *"a perceived lack of control over technology and a feeling of being overwhelmed by it"* (ibid.), whereas insecurity is *"distrust of technology, stemming from skepticism about its ability to work properly and concerns about its potential harmful consequences"* (ibid.). Discomfort and insecurity are inhibitors; i.e., factors that hinder technology readiness.

By using the two drivers and the two inhibitors of the TRI, Parasuraman & Colby [35] identify five clusters, namely: (1) explorers, who are highly tech-oriented, with a high degree of motivation and a low degree of resistance; (2) pioneers, who have both strong positive and negative views about technology; (3) skeptics, who have less extreme beliefs about technology; (4) hesitators, who are risk-averse and tend to have a very low degree of innovativeness; and (5) avoiders, who are tech-resistant and tend to have a low degree of motivation.

Since its first formulation, the TRI has been widely used to investigate the adoption of technologies in a variety of contexts, from internet banking (e.g., Ref. [36–38]), e-commerce and m-commerce (e.g., Ref. [39,40]) to e-learning (e.g., Ref. [41]) and e-government (e.g., Ref. [42,43]). The TRI has also been used to investigate mobile payments adoption in different countries and settings, for instance by integrating it with the TAM. Among others, this methodology has been used by Guhr et al. [8], who examine the perception and use of mobile payments by consumers in Finland, Germany, Japan and the US; by Shin & Lee [13], who study the intention to use NFC payments in South Korea; by Martens et al. [11], who investigate mobile payments adoption in Germany and South Africa; and by Rafdinal & Senalasari [12], who analyze the adoption of mobile payments apps during the COVID-19 pandemic in Indonesia.

Humbani & Wiese [9], for their part, combine TRI with convenience, compatibility, perceived cost and perceived risk to investigate consumers' readiness to adopt mobile payments in South Africa. In a later paper, also for South Africa, Humbani & Wiese [10] investigate both initial adoption and continued use of mobile payments apps, integrating constructs from the TRI and the Extended Expectation-Confirmation Model in the context of Information Technology (E-ECM-IT). Finally, Wiese & Humbani [14] cluster South African mobile payments users based on their TRI.

Another highly regarded theory that has been used to categorize consumers according to their technology adoption behavior is the Diffusion of Innovations (DOI) theory of Rogers [44]. Rogers proposed a diffusion of innovation curve, which identifies five adopter categories, namely: innovators, early adopters, early majority, late majority, and laggards. More specifically, adopters of a given technology are grouped accordingly to their innovativeness; i.e., *"the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than other members of a social system"* ([44], p. 245). In other words, innovativeness refers to the time at which an individual adopts a new technology. Even though there are certain similarities between the five TRI clusters and the five adopter categories of the DOI theory – especially between the "highest" clusters and the "earliest" categories (for example, between explorers and innovators) – we decided to rely on the TRI. The main reason is that we want to examine both adopters and non-adopters, and, where the latter are concerned, not just consumers who have not yet adopted mobile payment but will do so at a later stage, but also the "rejectors" as defined in Section 3.3.

3.2. Innovation resistance theory (IRT)

Where the second building block of our theoretical framework is concerned, the key tenet is that consumer resistance towards innovation is as important as acceptance and adoption behaviors [45]. This is particularly true when the diffusion rate of the innovation under study is relatively low, as is the case for mobile payment in Italy. In such cases, the traditional acceptance-based models might be inadequate, because the focus should be on understanding why consumers are *not* using the innovation, rather than on the reasons for adoption [20].

We therefore decided to focus our analysis on the barriers to the adoption and usage of mobile payments. We opted for the IRT as the central component of our model because it is the most frequently used theory when analyzing barriers to the adoption and usage of digital innovations, as it provides crucial information on how consumers react to them [21].[5]

The IRT was first formulated by Ram [28] and subsequently modified by Ram & Sheth [27]. The latter define innovation resistance as *"the resistance offered by consumers to an innovation, either because it poses potential changes from a satisfactory status quo or because it conflicts with their belief structure"* ([27], p. 6). The IRT identifies five barriers that obstruct the adoption of an innovation, which can be grouped into functional and psychological barriers.

Functional barriers emerge when consumers perceive significant changes resulting from the adoption of the innovation (o.c.). There are three functional barriers, namely: (1) the usage barrier, which refers to the usability of the innovation and the adjustments that consumers need to undergo to use it [19]; [27]; [21]; (2) the value barrier, which arises from the comparison of an innovation's performance and monetary worth with its alternatives [27]; and (3) the risk barrier, which is the degree of risk inherent in an innovation (o.c.).

Psychological barriers are more likely to arise if the innovation conflicts with consumers' prior beliefs (o.c.). According to the IRT, there exist two types, namely: (1) the tradition barrier, which arises when the innovation creates a cultural change for consumers, thereby requiring them to deviate from previously established traditions (o.c.); and (2) the image barrier, which occurs when the identity acquired by the innovation – based on the product category or the country of origin – creates a negative perception, leading to an undesirable image of the innovation itself (o.c.).

The IRT has been applied to investigate consumers' resistance towards mobile payments in different countries and settings. For instance, Kaur et al. [23] use IRT to analyze the barriers related to mobile payments in India, but focus on users' intention to use and recommend it. Talwar et al. [24], also for India, examine smartphone users who did *not* use mobile payments during the COVID-19 pandemic. Other authors integrate IRT with alternative IS theories or constructs. Ghosh [22], for example, adds habitual use of cash, surveillance, and "technology"[6] to IRT, and investigates the barriers to adoption among Indian consumers. Migliore et al. [46], for their part, integrate IRT with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to investigate the adoption gap between China and Italy.

3.3. Users, postponers, and rejectors

Importantly, consumers' technology adoption decision need not be final, and the decision is thus not "all or nothing". We therefore thought it interesting to examine gradations of (non-)adoption. In particular,

[5] Talwar et al. [21] review the literature on consumer resistance to digital innovations. They analyze 54 articles and find that 55 % used IRT as the basis for the empirical setting, while the remainder resorted to theories such as the DOI, the means-end approach, and the dual-factor perspective.

[6] "Technology" refers to poor connection in remote areas, low speed, weak signal, transmission failure and weak customer support [22].

innovation resistance can present itself in three forms: rejection, opposition or postponement [47]. Rejection is the strongest form of resistance and arises when consumers actively decide not to use the innovation [48]. Opposition is a form of rejection that occurs when the individual tends to resist the innovation, but is willing to try or test it before finally rejecting it [24,47–49]. Finally, postponement occurs when consumers prefer to wait and decide to delay adoption, even though they may consider the innovation acceptable [47,49].

Since opposition is a form of rejection [24,49], for the purpose of our analysis we follow Laukkanen [19] and model (1) *users* as consumers who have accepted mobile payment and use it; (2) *postponers* as non-users who have a behavioral intention to use mobile payment in the future; (3) *rejectors* as individuals who have decided not to use mobile payment *and* are not planning to do so in the future.

3.4. Research model and hypotheses

As explained, we applied the IRT to formulate a research model aimed at measuring the impact of the functional and psychological barriers on the decision to use mobile payments and on non-users' behavioral intention. Our analysis differs from previous studies because it tests the IRT first on the total sample and then across different types of consumers, which are identified based on their TRI.

In particular, we test the hypotheses by means of two binary logit models. The first model (the "adoption model") compares users and non-users, while the second (the "intention model") splits up the non-users into postponers and rejectors (and compares them). The independent variables are the five IRT barriers, as defined in section 3.2.

Extant studies show that the usage barrier is negatively associated with the intention to adopt and use digital innovations, such as mobile commerce [50]. In line with this, both Kaur et al. [23] and Ghosh [22] find that the usage barrier lowers the intention to adopt mobile payments for Indian consumers. Hence, H_1 reads:

H_{1a}: The usage barrier negatively impacts the usage of mobile payments.

H_{1i}: The usage barrier negatively impacts non-users' behavioral intention to use mobile payments.

Note that we use the subscripts “a” to refer to the adoption model and “i” to denote the intention model.

The second functional barrier is the value barrier. If an innovation does not provide any advantage compared to the existing products, then consumers are likely to resist it [22]. Extant studies confirm that the value barrier hinders the adoption of technologies such as mobile banking [19], mobile commerce [50], and mobile payments [22–24]. Accordingly, it is proposed that:

H_{2a}: The value barrier negatively impacts the usage of mobile payments.

H_{2i}: The value barrier negatively impacts non-users' behavioral intention to use mobile payments.

The third and final functional barrier is the risk barrier. If consumers perceive an innovation as risky, they may decide not to use it until they acquire additional knowledge about it [27]. Scholars have documented that the risk barrier can inhibit the adoption of mobile commerce [50] and mobile payments [23,24]. Thus, based on the existing literature, it is proposed that:

H_{3a}: The risk barrier negatively impacts the usage of mobile payments.

H_{3i}: The risk barrier negatively impacts non-users' behavioral intention to use mobile payments.

The tradition barrier is the first psychological barrier. Very often, consumers are used to certain routines [22]. If they are asked to deviate significantly from what they are accustomed to, the resistance towards the innovation is greater [27]. Previous studies have confirmed the negative relationship between the tradition barrier and the adoption of mobile commerce [50] and mobile payments [24]. Thus, we propose that:

H_{4a}: The tradition barrier negatively impacts the usage of mobile payments.

H_{4i}: The tradition barrier negatively impacts non-users' behavioral intention to use mobile payments.

The second and final psychological barrier is the image barrier. Consumers tend to associate an innovation with an image that can be derived from the innovation itself; for instance, the product class or industry, or the country of origin [27]. If the association is not favorable, consumers may resist the innovation (o.c.). The negative relation between the image barrier and mobile payment adoption has been confirmed by Ghosh [22] and Talwar et al. [24]. For this reason, it is posited:

H_{5a}: The image barrier negatively impacts the usage of mobile payments.

H_{5i}: The image barrier negatively impacts non-users' behavioral intention to use mobile payments.

Importantly, the main aim of the paper is to test the validity of the IRT across the identified clusters. Wiese & Humbani [14] cluster South African mobile payment users based on their TRI, showing that the clusters differ in terms of demographic characteristics *and* also in terms of mobile payment usage. Hence, consumers in different clusters may well value the IRT barriers differently. For instance, hesitators are highly risk-averse [35] and may, therefore, give more importance to the risk barrier. Similarly, avoiders are tech-resistant consumers, with a very low degree of motivation [35]. They may thus be more attached to tradition and to traditional payment instruments. As a consequence, for them the tradition barrier might be the greatest impediment. For these reasons, we propose that:

H_{6a}: The impact of the IRT barriers on the decision to use mobile payments differs across the identified clusters.

H_{6i}: The impact of the IRT barriers on the non-users' decision to postpone mobile payments differs across the identified clusters.

Fig. 1 schematically present the proposed research model. As mentioned at the beginning of the section, we perform two logit regressions based on the IRT, namely: the adoption model, which compares users and non-users, and the intention model, which delves deeper into the latter group to compare postponers and rejectors. Each model is then run for the total sample and for each cluster identified by using the TRI.

4. Method and data

Our target population is composed of adult (18+) Italian consumers. To collect the data, we designed a questionnaire that included constructs and scales derived from previous studies [19,35,46]; see Appendices A and Appendices B. To measure the items, we used a 5-point Likert scale, ranging from “strongly disagree” to “strongly agree”.

The questionnaire was administered in Italian. Since the questions drawn from the literature were in English, the questionnaire was first drafted in English and afterwards translated into Italian by the main author. The Italian version was then double-checked by Italian-speaking researchers from the department.

The questionnaire underwent two preliminary assessments, to evaluate face validity. The first pre-test was conducted with the help of Ipsos,

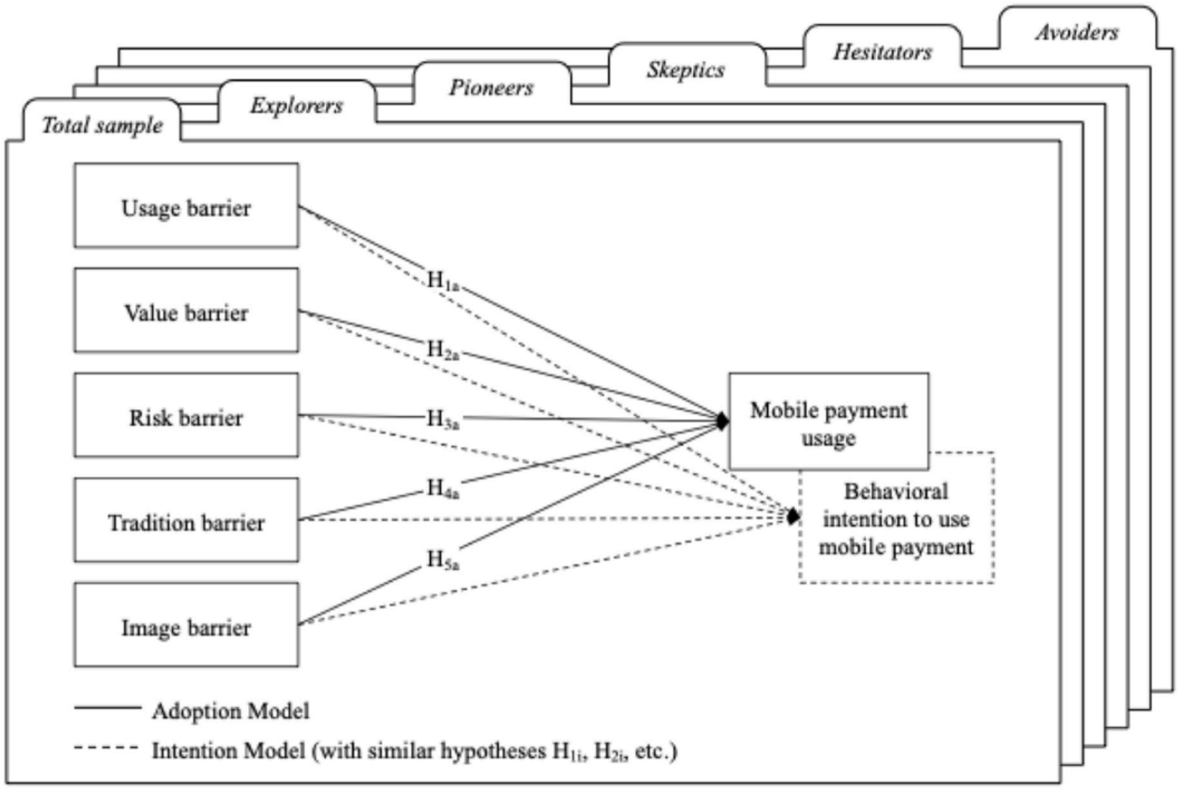

Fig. 1. The proposed research model.

a firm specialized in market research. The second was conducted with the main players of the Italian payment industry.[7] Based on the feedback received, changes were made to better reflect the context of the study and to ensure that the questions were understandable and relevant to respondents. We were also advised to decrease the number of questions in order to reduce respondent burden, a practice that is not uncommon in the literature [13,35,51,52]. Specifically, we limited the measurement of the TRI 2.0 to 12 items instead of 16, and we used 10 items to measure the IRT, instead of 14 (see Appendices A and Appendices B for a detailed justification of our choices).

The questionnaire was administered by Ipsos. To ensure representativeness, we resorted to quota controls for age, gender and region. The survey was carried out between November and December 2022, using the Computer-Assisted Web Interviewing (CAWI) methodology. A total of 2,000 answers were gathered. Of these, we maintained only the answers of respondents that are in a position to have access to mobile payments; i.e., consumers who own a smartphone and at least a bank account or a payment card. A total of 1,795 answers were considered valid. Analyses were performed using Stata 17 software.

5. Results

In this section, we first describe the sample. Subsequently, we discuss the assessment of the factors for the TRI and present the cluster analysis. The fourth and fifth subsection assess the factors for the IRT and discuss the results of the logit regressions.

5.1. Descriptive statistics

Table 1 provides an overview of the descriptive statistics. 51.7 % of the respondents are female, and the rest male, in line with the population of reference (according to data published by Istat[8] – the Italian statistical agency – 50.4 % of Italians aged 18 to 75 are female). The majority of the respondents are older than 45, with people between 18 and 33 years old and between 34 and 45 years old representing, respectively, 21.7 % and 22.2 %. This age distribution reflects that of the population. As for education, 17.7 % are highly educated, compared to 20.0 % of the Italian population in 2021.[7]

17.2 % of the respondents are mobile payment users, with 70 % of them preferring NFC wallets to apps. More in particular, 54 % of the users own an NFC wallet and no apps, 23 % have only a wallet based on other technologies, and the remainder (23 %) have both. As can be seen in Table 1, the Pearson χ^2 test shows that the distribution of gender, age and education is significantly different between users and non-users, with the percentages of male, young and highly educated persons being significantly higher among the first.

The behavioral intention to use mobile payment is measured with a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree". Following the definitions in Section 3.3, postponers are non-users with a behavioral intention to use mobile payment at least equal to 3. Conversely, rejectors are non-users with a behavioral intention lower than 3. With these definitions, postponers represent 68 % of all respondents, while rejectors account for 14.8 %. The shares of young people and the highly educated are significantly higher among

[7] The questionnaire was sent for a preliminary assessment to the following companies: Accenture, Agos, American Express, Banca Cambiano 1884, Banca di Asti, Banca Mediolanum, Banca Popolare di Sondrio, Banco BPM, Bancomat, Bibanca, BNL - Gruppo BNP Paribas, Cassa Centrale Banca, CRIF, CUSTOM, Deloitte, Deutsche Bank, Ennova, EY, HYPE, ING, Ingenico, Intesa Sanpaolo, Ipsos, Keyless, Klarna, Konvergence, LIS Holding, Market Pay, Mastercard, Mooney, N&TS GROUP, Nexi, PAX Italia, Pay Reply, PayDo, PayPal, Postepay, PwC, Q8, ReActive, Scalapay, Sinergia, Sparkasse – Cassa di Risparmio di Bolzano, UNGUESS, UniCredit, UnipolSai, Visa, Worldline and Zucchetti. Feedback was provided by several of the companies.

[8] http://dati.istat.it, accessed on July 31st, 2023.

Table 1
Descriptive statistics The assumptions for the Pearson χ^2 were met.

	Total sample	Mobile payment users	Mobile payment non-users		
				Mobile payment postponers	Mobile payment rejectors
Share	100 %	17.23 %	82.77 %	67.99 %	14.78 %
Gender					
Male	48.33 %	53.31 %	47.29 %	52.72 %	52.65 %
Female	51.67 %	46.69 %	52.71 %	47.28 %	47.35 %
		Pearson $\chi^2 = 4.451$ p-value = 0.035		Pearson $\chi^2 = 0.317$ p-value = 0.573	
Age					
18-33	21.68 %	30.85 %	19.77 %	21.90 %	9.97 %
34-45	22.22 %	28.18 %	20.98 %	22.25 %	15.16 %
46-59	30.95 %	24.20 %	32.36 %	31.15 %	37.91 %
60-75	25.15 %	16.78 %	26.89 %	24.71 %	36.96 %
		Pearson $\chi^2 = 35.511$ p-value ≤ 0.001		Pearson $\chi^2 = 30.4849$ p-value ≤ 0.001	
Education					
Low	40.73 %	29.04 %	43.16 %	41.37 %	51.39 %
Medium	41.60 %	46.46 %	40.59 %	41.87 %	34.73 %
High	17.67 %	24.50 %	16.25 %	16.76 %	13.89 %
		Pearson $\chi^2 = 0.228$ p-value ≤ 0.001		Pearson $\chi^2 = 11.4431$ p-value = 0.003	
Place of residence (number of inhabitants)					
< 5,000	16.11 %	13.40 %	16.68 %	16.27 %	18.55 %
5,001–10,000	15.23 %	14.43 %	15.40 %	14.72 %	18.53 %
10,001–30,000	23.63 %	23.31 %	23.68 %	24.42 %	20.30 %
30,001–100,0000	21.53 %	24.06 %	21.00 %	21.25 %	19.88 %
100,001–250,000	8.00 %	7.72 %	8.06 %	8.27 %	7.11 %
> 250,000	15.50 %	17.09 %	15.17 %	15.08 %	15.63 %
		Pearson $\chi^2 = 4.899$ p-value = 0.428		Pearson $\chi^2 = 3.5685$ p-value = 0.613	
Intention to use (or continue using) mobile payment					
Very low	5.11 %	–	6.17 %		34.57 %
Low	9.93 %	1.53 %	11.68 %		65.43 %
Neutral	31.19 %	12.52 %	35.08 %	42.70 %	
High	34.29 %	31.90 %	34.79 %	42.35 %	
Very high	19.47 %	54.05 %	12.28 %	14.94 %	
		Pearson $\chi^2 = 326.4327$ p-value ≤ 0.001			

postponers when compared to rejectors.

5.2. Assessment of TRI factor structure

In order to assess the general data structure, we first conducted a Principal Component Analysis (PCA) using Varimax Rotation of the factor loadings. The scree plot of Eigenvalues indicated a four-factor solution, as the contribution of each additional factor to the explained variance was relatively small. The third discomfort item, DIS3, was discarded as it had a factor loading below 0.5. Hence, we performed a second factor analysis, without DIS3. Again, the scree plot of Eigenvalues confirmed a four-factor solution, which explained 74 % of the variance in the items. We then computed the Kaiser-Meyer-Olkin Measure of Sampling Adequacy. This was equal to 0.84, which confirms that the data are suited for factor analysis.

Table 2 shows the factor loadings for the items, all of which are strong. The factors were named according to the literature. Reliability was checked by computing Cronbach's alphas for all constructs, which were all above (or very close to) the cut-off value of 0.7.

5.3. Cluster analysis

Several techniques of cluster analysis exist [53]. We opted for two-step cluster analysis because it can handle larger datasets than the traditional K-means approach and does not require the number of potential clusters to be determined a priori, as the technique can identify the optimal number [53].

Accordingly, the first step is a hierarchical clustering that allows to determine the most suited number of clusters, as well as the initial centers. The hierarchical clustering model was used to generate a dendrogram (see Appendix C), which graphically confirmed the five-cluster solution proposed by Parasuraman & Colby [35]. The second step is K-means clustering, starting from the centers (and with the number of clusters determined in the first step).

We used ANOVA to test for dissimilarities in the defining variables among clusters. Subsequently, we conducted Scheffé pairwise comparisons of means to establish whether pairs were significantly different. The five-cluster model met the criteria.

Overall, the analysis confirmed the five-cluster solution described in the literature, as shown in Table 3. We named the clusters following Parasuraman & Colby [35]; see Section 3.1 for details. Explorers score highest on innovativeness and optimism, and lowest on discomfort and insecurity. They represent 14.5 % of the respondents, and their level of education is significantly higher compared to the rest of the sample. Unsurprisingly, explorers have the highest share of mobile payment users of the five clusters (25.8 %). The behavioral intention to adopt mobile payment is also significantly higher (Pearson $\chi^2 = 106.8$; p-value

Table 2
Constructs of the TRI factor analysis and relative items, factor loadings, and Cronbach's alpha.

Construct	Item	Mean	Cronbach's alpha	Factor loading
Innovativeness	INN1	3.1511	0.8304	0.6024
	INN2	2.8530		0.5850
	INN4	3.5191		0.5095
Optimism	OPT1	3.8563	0.7841	0.6035
	OPT3	3.5225		0.5880
	OPT4	3.6633		0.5215
Discomfort	DIS2	2.7431	0.6804	0.7740
	DIS2	3.0473		0.6047
Insecurity	INS1	3.4699	0.816	0.5687
	INS2	3.5152		0.5676
	INS3	3.4965		0.5683

Table 3
Descriptive statistics and cluster distribution results.

	Total sample	CLUSTERS				
		Explorers	Pioneers	Skeptics	Hesitators	Avoiders
Share	100 %	14.48 %	20.66 %	26.24 %	17.22 %	21.40 %
TRI CONSTRUCTS (mean values)						
Innovativeness	−0.043	1.467	0.799	0.554	−1.038	−1.808
Optimism	−0.024	1.413	0.497	0.444	−0.903	−1.367
Discomfort	0.013	−1.281	1.303	−0.670	−0.178	0.636
Insecurity	0.004	−2.226	0.815	0.375	−1.179	1.229
GENDER						
Male	48.33 %	51.26 %	53.24 %	51.72 %	49.28 %	36.68 %
Female	51.67 %	48.74 %	46.76 %	48.28 %	50.72 %	63.32 %
AGE						
18-33	21.68 %	22.16 %	27.61 %	20.68 %	24.94 %	14.21 %
34-45	22.22 %	25.91 %	22.42 %	24.11 %	19.23 %	19.63 %
46-59	30.95 %	31.94 %	28.89 %	31.19 %	27.35 %	34.88 %
60-75	25.15 %	19.99 %	21.08 %	24.02 %	28.49 %	31.28 %
EDUCATION						
Low	40.73 %	27.04 %	36.76 %	37.33 %	41.42 %	57.42 %
Medium	41.60 %	50.23 %	42.14 %	44.83 %	41.30 %	31.54 %
High	17.67 %	22.73 %	21.10 %	17.84 %	17.27 %	11.04 %
PLACE OF RESIDENCE (number of inhabitants)						
< 5,000	16.11 %	16.13 %	9.67 %	15.74 %	19.94 %	19.71 %
5,001–10,000	15.23 %	10.54 %	16.11 %	14.95 %	15.28 %	17.85 %
10,001–30,000	23.63 %	16.00 %	25.48 %	27.21 %	22.58 %	23.41 %
30,001–100,0000	21.53 %	25.19 %	22.86 %	21.75 %	20.42 %	18.39 %
100,001–250,000	8.00 %	10.33 %	9.24 %	6.84 %	7.88 %	6.76 %
> 250,000	15.50 %	21.81 %	16.63 %	13.51 %	13.91 %	13.87 %
MOBILE PAYMENT						
Users	17.23 %	25.82 %	24.79 %	17.28 %	14.70 %	6.10 %
Non-users	82.77 %	74.18 %	75.21 %	82.72 %	85.30 %	93.90 %
Postponers	67.99 %	68.13 %	66.98 %	70.66 %	68.99 %	64.82 %
Rejectors	14.78 %	6.04 %	8.24 %	12.07 %	16.31 %	29.08 %
INTENTION TO USE MOBILE PAYMENT						
Very low	5.11 %	2.00 %	1.63 %	3.25 %	4.97 %	12.96 %
Low	9.93 %	4.05 %	7.06 %	9.23 %	11.71 %	16.13 %
Neutral	31.19 %	19.17 %	29.25 %	28.57 %	37.53 %	39.33 %
High	34.29 %	33.50 %	37.21 %	40.79 %	33.18 %	24.95 %
Very high	19.47 %	41.30 %	24.85 %	18.16 %	12.62 %	6.64 %

The mean values for TRI constructs are not in the 1-to-5 scale since they have been computed using PCA.

≤0.001). Pioneers represent 20.7 % of the respondents. The share of males and young people is significantly higher compared to the rest of the sample. At 24.8 %, the share of mobile payment users is significantly above the average (and only slightly lower compared to the explorers). Skeptics number 26.2 %. They reflect the average of the sample in terms of gender, age, education level, dimension of the place of residence, and share of mobile payment users. However, they stand out in two respects: (1) they have an above-average intention to use mobile payment, and (2) the postponers significantly outnumber the rejectors. This clearly fits the nature of skeptics. Hesitators are good for 17.2 % of the respondents. Similar to avoiders, they significantly differ from the rest of the sample only because of their lower behavioral intention to use. Finally, avoiders represent 21.4 %. At 63.3 %, females are overrepresented in this cluster. The same is true for people older than 45 and those with a lower level of education. Unsurprisingly, avoiders have the lowest share of users and the highest percentage of rejectors.

5.4. Assessment of IRT factor structure

To assess the general data structure in terms of the IRT, we again conducted a PCA using Varimax Rotation of the factor loadings. The two value barrier items (VB1 and VB2) have a low correlation (0.3279) and a low Cronbach's alpha (0.4939), showing that the reliability of the factor is an issue. For this reason, we decided to maintain VB1 and VB2 as stand-alone variables. The poor internal consistency of the value barrier scale might be due to the phrasing of the items (see Appendix B). In particular, VB1 refers to the general advantages that mobile payments might provide, while VB2 specifically refers to the possibility to better control one's spending. Since both items represent a comparison of mobile payments' performance with its alternatives, H_{2a} and H_{2i} are divided into two hypotheses and rephrased as follows:

H_{2a*}: VB1 negatively impacts the usage of mobile payments.

H_{2a**}: VB2 negatively impacts the usage of mobile payments.

H_{2i*}: VB1 negatively impacts non-users' behavioral intention to use mobile payments.

H_{2i**}: VB2 negatively impacts non-users' behavioral intention to use mobile payments.

Next, we ran a second PCA, maintaining only the factors related to the remaining four barriers. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy is equal to 0.8081, showing that the data are suited for factor analysis. The factor loadings for the items are all strong, as shown

Table 4
Constructs of the IRT factor analysis and relative items, factor loadings, Cronbach's alpha and Loevinger's H coefficients.

Construct	Item	Mean	Factor loading	Cronbach's alpha	Loevinger's H coefficients
Usage barrier	UB1	2.3742	0.6830	0.8552	0.76
	UB2	2.3834	0.7150		
Value barrier	VB1	3.0584	–	0.4939	
	VB2	2.8481	–		
Risk barrier	RB1	3.1062	0.8016	0.7430	0.61
	RB2	3.0170	0.5909		
Tradition barrier	TB1	3.0661	0.6536	0.8375	0.76
	TB2	3.2355	0.7508		
Image barrier	IB1	2.7849	0.7435	0.8368	0.76
	IB2	2.6363	0.6546		

in Table 4. The factors were named according to the literature.

Finally, we assessed the reliability, convergent validity and discriminant validity of the multi-item scales using the "validscale" command in Stata [54]. Reliability was checked by computing the Cronbach's alphas – which are all above the cut-off value of 0.7 – and the Loevinger's H coefficients – which are all greater than the threshold of 0.3 (Table 4). Convergent validity and discriminant validity were assessed using the correlation matrix.

5.5. IRT regression analysis

We tested the proposed hypotheses by running two logistic regressions. In the first model, the dependent variable is "mobile payment user", which is equal to 1 if the respondent has used mobile payments at least occasionally in the past year, and equal to 0 otherwise. In the second, the dependent variable is "mobile payment postponer", which is equal to 1 if the respondent is a postponer and equal to 0 if the respondent is a rejector. In both models the independent variables are "usage barrier", "risk barrier", "tradition barrier", and "image barrier" – together with VB1 and VB2 as standardized stand-alone variables (see 5.4).

For the full sample, results are shown in Table 5. We assessed the goodness-of-fit of the models by computing the Nagelkerke R^2, the -2 Log Likelihood, the Chi-square value, and the Hosmer-Lemeshow test, which all indicate a good fit (Table 5). In addition, we also checked for multicollinearity, classification tables, and outliers; the results were reassuring.[9] The results of the first model support hypotheses H_{1a}, H_{2a**}, H_{3a}, H_{4a}, whereas hypotheses H_{2a*} and H_{5a} are not supported. More specifically, the odds ratios show that tradition barrier is the greatest obstacle to mobile payment usage. Conversely, VB1 does not significantly affect usage. Surprisingly, the image barrier has a significant positive effect on usage.

In the second model, H_{1i}, H_{2i*}, H_{2i**}, H_{4i} are supported, whereas H_{3i} and H_{5i} are not. In this case, the risk and image barriers do not play a significant role, while VB1 has a significant negative impact.

Subsequently, we tested the models in every cluster. Tables 6 and 7 present an overview of the results for the first and the second model, respectively. They show whether the independent variables have a statistically significant effect on the dependent variable, in the total sample as well as in each of the subsamples. Detailed results for both models, together with goodness-of-fit indices, are reported in Appendix D. Importantly, the results are different for the total sample and the clusters, thereby supporting H_{6a} and H_{6i}.

6. Discussion

6.1. Impact of the IRT barriers in the total sample

The objective of the paper is to analyze which barriers prevent consumers from using mobile payment instruments. The analysis assumes that consumers have a certain level of resistance against innovations and theorizes that the five adoption barriers identified by the IRT help explain this resistance.

First, the usage barrier has the expected negative impact on the use of mobile payments (see Table 5). As explained in the literature review, the usage barrier arises when the innovation requires consumers to change their habits. The greater the required adjustment, the greater the resistance. Traditional payment instruments, such as cash, are still widespread in Italy, and paying with cash remains a habit for the majority of consumers, implying that switching to mobile payment requires a significant adjustment. van der Cruijsen et al. [55], in a study for the Netherlands, find that changing payment behavior is challenging, especially when consumers are used to pay with cash. Our result is also consistent with the findings of previous studies on mobile payment [22, 23]. The usage barrier also has a negative impact on non-users' behavioral intention (see Table 7). If consumers perceive that using mobile payment requires a great adjustment, they do not develop a behavioral intention to use it.

Interestingly, VB1 does not play a significant role in inhibiting consumers from using mobile payment methods, whereas VB2 does (see Table 5). At the same time, both VB1 and VB2 push non-users towards rejection, rather than postponement (see Table 7). The latter results suggest that if non-users perceive that mobile payment might be of value, they develop a behavioral intention to use it. This is true regardless of whether the benefit is general (VB1) or specific (VB2)[10]. Instead, the results of the first model suggest that when deciding whether to actually use mobile payment or not, consumers value specific benefits, such as the possibility to better control their own spending. In other words, when it comes to actually use of the technology, consumers value the technology yielding the specific benefit they are interested in.

The third significant barrier identified by the analysis in Table 5 is the risk barrier. If consumers perceive mobile payment as risky, they will refrain from using it. This result is in line with previous literature [23, 24]. Interestingly, the impact of the risk barrier is not significant in the second model. This suggests that the importance of perceived risk is low when merely evaluating the eventual possibility of adopting a technology but increases when the decision becomes real.

The tradition barrier, for its part, has a negative effect on both mobile payment usage and postponement. The use of cash is still predominant in Italy. In 2021, cash accounted for 76 % of the total number of B2C transactions, compared to 22 % for cards and mobile payment, and 2 % for other payment instruments such as bank transfers and checks [56]. This suggests that starting to use a cashless instrument may require a cultural change for consumers, thereby constituting a barrier. This result contrasts with the papers of Ghosh [22] and Kaur et al. [23], which both find the tradition barrier to play no significant role in inhibiting, respectively, mobile payments adoption and intention to use. However, both studies examine the Indian context, where mobile payment usage is more widespread compared to Italy [7]. Italian consumers may thus well perceive mobile payments as a bigger cultural change.

The image barrier does not significantly affect the decision to postpone or reject usage. It does, however, have a significant and positive impact on the decision to use mobile payment. In a way, this finding is in line with extant literature, in that it confirms that further investigation is needed. Indeed, previous studies also found mixed results: Ghosh [22] and Talwar et al. [24] confirm the negative impact of the image barrier, whereas Kaur et al. [23] and Migliore et al. [46] found no significant relation.

Finally, our study is related to Migliore et al. [46], in that they also analyze mobile payment in Italy. However, unlike us, Migliore et al. [46] integrate IRT with UTAUT2 and, most importantly, they focus on users and thus, in fact, examine continuance intention rather than initial intention to adopt. They find that for Italian users the tradition barrier is the only impediment to continued use of mobile payment, while the other barriers are not significant. This difference in results might be due to the different variable of interest: the fact that consumers already use mobile payment might mean that they have already overcome some of the barriers, therefore rendering them insignificant.

6.2. Impact of the IRT barriers on the level of the clusters

An important contribution of the paper is that it also aims to verify

[9] More detailed results can be obtained upon request from the corresponding author.

[10] As mentioned in Section 5.4, VB1 refers to general advantages that mobile payment instruments may provide compared to other payment instruments. Conversely, VB2 specifically refers to the possibility granted by mobile payments to better control one's spending.

Table 5
Logistic regression results for the full sample. ✓ indicates that the variable has a significant negative impact on the dependent variable; × shows that the variable has a significant positive effect on the dependent variable.

Independent variables	Mobile payment users vs non-users			Mobile payment postponer vs rejectors		
	Sig.	Coefficient	Odds ratio	Sig.	Coefficient	Odds ratio
Usage barrier	✓***	−0.3707	0.6903	✓***	−0.7183	0.4876
VB1		−0.1156	0.8908	✓***	−0.3042	0.7377
VB2	✓***	−0.4572	0.6331	✓***	−0.4734	0.6229
Risk barrier	✓***	−0.3303	0.7187		0.0539	1.0554
Tradition barrier	✓***	−0.1957	0.8222	✓***	−0.2543	0.7755
Image barrier	×**	0.1761	1.1926		−0.0190	0.9812
Constant	✓***	−1.9227	0.1462	✓***	2.3540	10.5278
GOODNESS-OF-FIT						
Nagelkerke R^2:	0.2280			0.3540		
−2 Log Likelihood:	686.0871			512.3746		
Chi-squared value:	263.0710	p-value:	≤0.001	357.1110	p-value:	≤0.001
Hosmer-Lemeshow test:	11.4100	p-value:	0.1794	12.3800	p-value:	0.1350

*** p-value <0.01; ** p-value <0.05; * p-value <0.10.

Table 6
Logistic regression results for each cluster. Dependent variable: mobile payment user. ✓ indicates that the variable has a significant negative impact on the dependent variable; × shows that the variable has a significant positive effect on the dependent variable.

Mobile payment users vs non-users	Total sample	Explorers	Pioneers	Skeptics	Hesitators	Avoiders
	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.
Usage barrier	✓***	✓**	✓***	✓**		✓*
VB1						
VB2	✓***	✓**	✓**	✓**		
Risk barrier	✓***			✓***	✓***	
Tradition barrier	✓***	✓*		✓**		
Image barrier	×**					
Constant	✓***	✓***	✓***	✓***	✓***	✓***

*** p-value <0.01; ** p-value <0.05; * p-value <0.10.

Table 7
Logistic regression results for each cluster. Dependent variable: mobile payment postponer. ✓ indicates that the variable has a significant negative impact on the dependent variable; × shows that the variable has a significant positive effect on the dependent variable.

Mobile payment postponers vs rejectors	Total sample	Explorers	Pioneers	Skeptics	Hesitators	Avoiders
	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.
Usage barrier	✓***		✓***	✓***	✓***	✓***
VB1	✓***	✓*				
VB2	✓***	✓***		✓*	✓***	✓*
Risk barrier						×**
Tradition barrier	✓***	×**		✓**		✓***
Image barrier						
Constant	×***	×***	×***	×***	×***	×***

*** p-value ≤0.01; ** p-value <0.05; * p-value <0.10.

the validity of the IRT across the clusters, so as to determine whether there are conditions under which the theory is no longer valid.

The only barriers for which the results for all clusters are the same as for the full sample are VB1 in the first model (in Table 6) and the image barrier in the second model (in Table 7), in that the barriers are never significant. In all other cases, there are differences – which demonstrates the value added of our cluster analysis. Overall, the barriers that remain valid in the highest number of clusters are the usage barrier (significant in three clusters in the first model and in four in the second) and VB2 (significant in, respectively, three and two clusters).

We now discuss the results per cluster. Explorers and pioneers are both tech oriented. As such, when deciding whether to use mobile payments, they are not bothered by the risk, tradition,[11] and image barriers. Conversely, they do value the advantages provided by the technology (VB2), as well as its usability (usage barrier). In line with this, the only barrier that fosters rejection among non-user pioneers is the usability of the technology; VB2, however, is no longer significant. This suggests that pioneers first evaluate the effort that is required to use a technology and only afterwards – i.e., when deciding whether to actually use it – consider the value provided. Explorers, instead, take into account VB2 also when forming a behavioral intention to adopt the technology, whereas VB1 is significant only at the 10 % level. Moreover, the tradition barrier has a significant *positive* effect on their decision to postpone or reject mobile payment. This suggests that explorers are more willing to try a new technology if they perceive it to be disruptive, which confirms their higher attitude towards technology.

Skeptics are the less extreme consumers, who reflect the average respondents in terms of both demographic characteristics and mobile payment usage. The same barriers that are significant at the full sample level are also significant for them, barring the image barrier. However, when they consider whether to reject or postpone usage, VB2 is significant at the 10 % level only.

Hesitators are risk averse and tech resistant. Unsurprisingly, in this

[11] [1]The tradition barrier is only significant at the 10 % level for explorers.

cluster the risk barrier is the only significant barrier to usage. Rejection is fostered by the usage barrier and VB2.

Finally, avoiders are tech-resistant to the point that they do not consider any of the barriers when deciding upon usage.[12] However, this result should be treated with caution, since the Hosmer-Lemeshow test yielded a p-value of 0.0035, suggesting poor goodness-of-fit of the model. Where avoiders' decision to postpone or reject is concerned, the tradition barrier is significant. Interestingly, in the second model the risk barrier is not only significant, unlike for the total sample, but also positive. That is, if the technology is perceived to be risky, then non-user avoiders form a behavioral intention to adopt, instead of reject, it.

Finally, in the first model the image barrier is not significant in any of the clusters. The same is true for VB1 in the second model.

6.3. Theoretical contributions

The paper tested the classic IRT model in a developed country, namely Italy, where the usage of mobile payments is still low. We first tested the IRT model in the total sample, to assess what are the barriers to, respectively, usage and postponement of mobile payment. Then, we combined the IRT with cluster analysis based on the TRI, in response to Lee et al. [25]. Our theoretical contributions are as follows.

First, the empirical analysis shows that the IRT yields different results when applied to behavioral intention (model 2) or actual usage of mobile payment (model 1). More specifically, the risk and image barriers do not play a significant role for the behavioral intention of non-users, whereas VB1 is not considered a barrier when deciding whether to use mobile payment. This adds to the literature by further confirming that behavioral intention and actual usage are different behaviors, and that the barriers which affect them may well differ. Therefore, scholars are encouraged to thoroughly select the variable of interest. Specifically, it could be selected according to the life cycle stage the technology is in. For instance, when a technology is still in its infancy and is still rather unknown in the market, it might be more interesting to investigate which barriers prevent consumers from building a behavioral intention to adopt it. Conversely, when the technology starts spreading, it could be more fruitful to investigate which factors hinder usage, hence the switch from simple behavioral intention to actual usage.

Second, the two items of the value barrier – VB1 and VB2 – turned out to be not correlated, which suggests that there is a difference between specific and general value, at least where mobile payment is concerned. This is confirmed by the results of the two models. Apparently, a general benefit is important when consumers consider whether to adopt a technology, but no longer when deciding upon actual usage. In the latter case, individuals value the presence of specific benefits and a generic statement about potential values is no longer enough.

Finally, the different results obtained for the different segments confirm that cluster analysis does indeed enrich the IRT. Consumers have different attitudes towards technology in general, and this affect the factors they value when, respectively, forming an intention to use and deciding whether to actually use a specific innovation. Therefore, further studies should consider including segmentation of consumers when analyzing their behavior.

6.4. Practical contributions

From a practical perspective, the study provides knowledge about the factors that can help mobile payment providers increase the reach of their products.

First, as mentioned, our analysis shows that the factors that affect behavioral intention and actual usage are different. Hence, providers should adapt their strategies accordingly. In this regard, the study suggests that usability is a barrier to both behavioral intention and actual usage. The usage barrier refers to the effort that a user has to make in order to use the innovation. Thus, providers could try to develop easy-to-use products with a straightforward user experience, so that their usage does not bring drastic changes to users' daily payment habits. For instance, they could give users the possibility to customize the access to the selected mobile payment method. An option – for NFC wallets – could be to launch the payment app automatically when the smartphone is brought closer to the card reader. The customer would then be only required to authorize the payment. This would allow providers to ensure a user experience very similar to the one of contactless cards, thereby reducing the adjustments required from the consumer.

The tradition barrier is also significant in both models. This might be more difficult to overcome for mobile payment providers, because it has to do with consumers' habits and cultural background. However, the importance of the barrier suggests that it should be tackled to raise the usage of mobile payments. An important role could be played by public institutions, which could develop policies to increase the awareness among consumers of the importance and benefits provided by mobile payment instruments.

The results on the value barrier are mixed. On the one hand, mentioning generic benefits provided by mobile payment helps non-users in forming a behavioral intention to adopt it. On the other hand, generic benefits are no longer enough when it comes to usage. This suggests that mobile payment providers should try to understand the needs of consumers and try to provide products that answer those specific needs. Providers could also exploit communication campaigns to highlight the benefits provided by their products.

Further, the risk barrier is a significant impediment to actual usage only. Hence, when the goal is to foster usage, mobile payment providers are encouraged to also focus on factors that make users feel secure while paying with their smartphones. In doing so, providers should guarantee the safety of their products and clearly communicate this to their customers, thereby reassuring them.

Finally, and crucially, given the importance of the clusters, the above suggestions are likely to be more effective if targeted to a segment of consumers, instead of everyone without distinctions. Providers could tailor their marketing campaigns depending on the targeted cluster. For instance, if avoiders are more likely to use traditional means of information, such as newspapers or television, providers can play down the barriers that hinder usage – or behavioral intention – by avoiders on those channels.

7. Conclusions and limitations

Barriers to mobile payment usage are still a rather unexplored topic in the literature. Thus, our study applied the IRT to the Italian context, to investigate which factors are preventing consumers from both developing a behavioral intention to use and actually using mobile payment services.

The main limitations of the study concern the data gathering and the construct design. Specifically, the survey was carried out using the CAWI methodology and, hence, targeted consumers who are somehow already familiar with basic digital instruments, such as personal computers. Moreover, in view of the length of the original questionnaire, we were advised to reduce the number of questions, and therefore the number of items. Despite not being uncommon in the literature, future research might include the dropped items in order to improve the generalizability of the results.

The analysis provides practical implications by highlighting the barriers that both mobile payment providers and public institutions should tackle to enhance mobile payment usage in Italy.

From a theoretical perspective, we first empirically tested the IRT on the decisions to postpone and to use mobile payment, finding that the validity of the IRT changes depending on the setting. Further, we find that the two items previously used in extant studies to measure the value

[12] The only exception is the usage barrier which is significant only at the 10 % level.

barrier apparently do not fit the context of mobile payment usage in Italy, indicating that future studies should adapt the phrasing of the items to the technology under investigation. We also find that generic and specific benefits play different roles.

Finally, and most importantly, the results show that cluster analysis does enrich the IRT, thereby suggesting for future research that segmenting consumers adds value when investigating the barriers to adoption and use of a technology.

CRediT authorship contribution statement

Giulia Spinelli: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Luca Gastaldi:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Leo Van Hove:** Writing – review & editing, Visualization, Supervision, Methodology, Conceptualization. **Ellen Van Droogenbroeck:** Writing – review & editing, Visualization, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of Competing interest

None.

Data availability

Data will be made available on request.

APPENDIX A

Table A1
Measurement scales for TRI

Construct	Item		Reference
Optimism	OPT1	New technologies contribute to a better quality of life.	Parasuraman & Colby [35]
	OPT2	*Technology gives me more freedom of mobility. (dropped)*	
	OPT3	Technology gives people more control over their daily lives.	
	OPT4	Technology makes me more productive in my personal life.	
Innovativeness	INN1	Other people come to me for advice on new technologies.	Parasuraman & Colby [35]
	INN2	In general, I am among the first in my circle of friends to acquire new technology when it appears.	
	INN3	*I can usually figure out new high-tech products and services without help from others. (dropped)*	
	INN4	I keep up with the latest technological developments in my areas of interest.	
Discomfort	DIS1	Sometimes, I think that technology systems are too complicated.	Parasuraman & Colby [35]
	DIS2	Technical support lines are not helpful.	
	DIS3	Sometimes, I think that technology systems are not designed for ordinary people.	
	DIS4	*There is no such thing as a manual for a high-tech product or service that's written in plain language. (dropped)*	
Insecurity	INS1	People are too dependent on technology to do things for them.	Parasuraman & Colby [35]
	INS2	Too much technology distracts people to a point that is harmful.	
	INS3	Technology lowers the quality of relationships by reducing personal interaction.	
	INS4	*I do not feel confident doing business with a place that can only be reached online. (dropped)*	

Note: We dropped item OPT2 because it refers to the freedom of mobility, which can be specific to certain types of technology, whereas the TRI is supposed to measure technology in general; item INN3 because it refers to the possibility of receiving help from others; item DIS4 since the usage of manuals for technology products is becoming more and more outdated; and item INS4 as it is specific to e-commerce and m-commerce.

APPENDIX B

Table B1
Measurement scales for IRT. [a]Reversed scale

Construct	Measure item		Reference
Usage barrier	UB1	In my opinion, mobile payments are easy to use.[a]	Laukkanen [19]
	UB2	In my opinion, mobile payments are convenient.[a]	
	UB3	*In my opinion, mobile/Internet banking services are fast to use [a]. (dropped)*	
	UB4	*In my opinion, progress in mobile/Internet banking services is clear [a]. (dropped)*	
	UB5	*The use of changing PIN codes in mobile/Internet banking services is convenient [a]. (dropped)*	
Value barrier	VB1	In my opinion, mobile payments do not offer any advantage compared to other payment instruments.	Laukkanen [19]
	VB2	In my opinion, the use of mobile payments increases my ability to control my spending.[a]	
Risk barrier	RB1	I fear that while I am using mobile payments, the connection will be lost.	Laukkanen [19]
	RB2	I fear that mobile payments are not safe to use.	
	RB3	*I fear that the list of PIN codes may be lost and end up in the wrong hands. (dropped)*	
Tradition barrier	TB1	I prefer cash to mobile payments.	Migliore et al. [46]
	TB2	I think that cash gives a better feeling of my financial means.	
Image barrier	IB1	In my opinion, new technology is often too complicated to use.	Laukkanen [19]
	IB2	I believe that mobile payments are too difficult to be useful.	

Note 1: The items derived from Laukkanen [19] were originally phrased to investigate Internet and mobile banking. The phrasing has been slightly changed to adapt it to the context of mobile payments.

Note 2: We dropped UB3 because an increased speed granted by mobile payments might be perceived by respondents as value-added, therefore making it similar to the value barrier; UB4 because mobile payments are still a relatively new and unknown technology in Italy and respondents might find it difficult to evaluate its progress; UB5 because the majority of mobile payments services do not involve the use of changing PIN codes; RB3 because the list of PIN codes relates more to (physical) payment cards, while the majority of mobile payments solutions resort to the smartphone PIN code or biometric authentication (such as face or fingerprint scan).

APPENDIX C

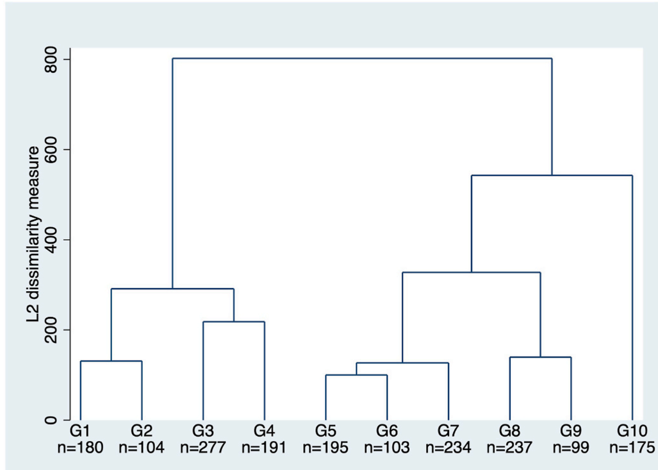

Fig. C1. – Dendrogram generated by the hierarchical clustering model.

APPENDIX D

Table D1
Logistic regression results for each cluster. Dependent variable: mobile payment user. p-values in brackets.

Independent variables	Total sample	Explorers	Pioneers	Skeptics	Hesitators	Avoiders
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Usage barrier	−0.3707 (≤0.001)	−0.4823 (0.0390)	−0.4738 (0.0020)	−0.3890 (0.0460)	−0.1392 (0.3860)	−0.5371 (0.0630)
VB1	−0.1156 (0.2230)	−0.1492 (0.5900)	−0.1028 (0.5850)	−0.2409 (0.2040)	−0.3597 (0.1540)	−0.0947 (0.7290)
VB2	−0.4572 (≤0.001)	−0.5195 (0.0320)	−0.4080 (0.0230)	−0.4573 (0.0290)	0.0147 (0.9490)	−0.4039 (0.1890)
Risk barrier	−0.3303 (≤0.001)	−0.2495 (0.2330)	−0.0960 (0.5390)	−0.4788 (0.0050)	−0.6197 (0.0030)	−0.1032 (0.6910)
Tradition barrier	−0.1957 (0.0050)	−0.3211 (0.0580)	−0.2388 (0.1100)	−0.2938 (0.0300)	0.1152 (0.5290)	0.0149 (0.9440)
Image barrier	0.1761 (0.0260)	0.0374 (0.8710)	0.1771 (0.2400)	−0.0815 (0.6680)	0.2939 (0.1500)	−0.2109 (0.4370)
Constant	−1.9227 (≤0.001)	−2.5634 (≤0.001)	−1.4799 (≤0.001)	−2.4090 (≤0.001)	−1.9361 (≤0.001)	−2.6600 (≤0.001)
GOODNESS-OF-FIT						
Nagelkerke R^2	0.2280	0.3360	0.1800	0.3480	0.1060	0.1810
−2 Log Likelihood	686.0871	113.0217	181.8873	159.7333	118.4927	74.3438
Chi-square value	263.0710 (≤0.001)	68.3380 (≤0.001)	47.8460 (≤0.001)	110.2730 (≤0.001)	18.870 (0.0040)	26.2750 (≤0.001)
Hosmer-Lemeshow	11.4100 (0.1794)	12.5800 (0.0831)	4.7800 (0.7813)	7.4300 (0.4906)	11.4700 (0.1766)	22.9200 (0.0035)

Table D2
Logistic regression results for each cluster. Dependent variable: mobile payment postponer. P-values in brackets.

Independent variables	Total sample	Explorers	Pioneers	Skeptics	Hesitators	Avoiders
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Usage barrier	−0.7183 (≤0.001)	−0.1415 (0.6410)	−1.6229 (≤0.001)	−0.6624 (0.0010)	−0.4484 (0.0070)	−0.8335 (≤0.001)
VB1	−0.3042 (0.0060)	−0.8879 (0.0640)	−0.4010 (0.2600)	−0.3483 (0.1740)	−0.3418 (0.1830)	−0.3001 (0.1140)
VB2	−0.4734 (≤0.001)	−1.6114 (0.0040)	0.1795 (0.5390)	−0.4523 (0.0630)	−0.7059 (0.0040)	−0.3236 (0.0890)
Risk barrier	0.0539 (0.5800)	−0.1770 (0.5690)	−0.1873 (0.5660)	−0.1932 (0.3790)	−0.1232 (0.5670)	0.4296 (0.0220)
Tradition barrier	−0.2543 (0.0010)	0.6553 (0.0250)	−0.3813 (0.2170)	−0.3782 (0.0200)	0.2580 (0.1770)	−0.4931 (0.0010)
Image barrier	−0.0190 (0.8190)	−0.0500 (0.8460)	0.1964 (0.5590)	−0.0105 (0.9520)	−0.1860 (0.3770)	0.0068 (0.9660)
Constant	2.3540 (≤0.001)	3.4617 (≤0.001)	3.6518 (≤0.001)	2.5062 (≤0.001)	2.3767 (≤0.001)	1.9764 (≤0.001)
GOODNESS-OF-FIT						
Nagelkerke R^2	0.3540	0.4710	0.4520	0.3480	0.2600	0.3840
−2 Log Likelihood	512.3746	32.0971	60.2418	118.0669	104.7819	164.9662
Chi-square value	357.1110 (≤0.001)	43.7440 (≤0.001)	70.5380 (≤0.001)	84.7660 (≤0.001)	45.5810 (≤0.001)	112.6420 (≤0.001)
Hosmer-Lemeshow	12.3800 (0.1350)	0.9100 (0.9987)	9.5700 (0.2963)	5.2300 (0.7325)	4.7500 (0.7837)	9.3500 (0.3139)

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