information

Article

A Comparative Study of Users versus Non-Users' Behavioral Intention towards M-Banking Apps' Adoption

Vaggelis Saprikis [1,*], Giorgos Avlogiaris [2] and Androniki Katarachia [3]

1 Department of Management Science and Technology, University of Western Macedonia, 50100 Kozani, Greece
2 Department of Statistics and Insurance Science, University of Western Macedonia, 51100 Grevena, Greece; aff00084@uowm.gr
3 Department of Accounting and Finance, University of Western Macedonia, 50100 Kozani, Greece; akatarachia@uowm.gr
* Correspondence: esaprikis@uowm.gr

Abstract: The banking sector has been considered as one of the primary adopters of Information and Communications Technologies. Especially during the last years, they have invested a lot into the digital transformation of their business process. Concerning their retail customers, banks realized very early the great potential abilities to provide value added self-services functions via mobile devices, mainly smartphones to them; thus, they have invested a lot into m-banking apps' functionality. Furthermore, the COVID-19 pandemic has brought out different ways for financial transactions and even more mobile users have taken advantage of m-banking app services. Thus, the purpose of this empirical paper is to investigate the determinants that impact individuals on adopting or not m-banking apps. Specifically, it examines two groups of individuals, users (adopters) and non-users (non-adopters) of m-banking apps, and aims to reveal if there are differences and similarities between the factors that impact them on adopting or not this type of m-banking services. To our knowledge, this is the second scientific attempt where these two groups of individuals have been compared on this topic. The paper proposes a comprehensive conceptual model by extending Venkatech's et al. (2003) Unified Theory of Acceptance and Use of Technology (UTAUT) with ICT facilitators (i.e., reward and security) and ICT inhibitors (i.e., risk and anxiety), as well as the recommendation factor. However, this study intends to fill the research gap by investigating and proving for the first time the impact of social influence, reward and anxiety factors on behavioral intention, the relationship between risk and anxiety and the impact of behavioral intention on recommendation via the application of Confirmatory Factor Analysis and Structural Equation Modeling (SEM) statistical techniques. The results reveal a number of differences regarding the factors that impact or not these two groups towards m-banking app adoption; thus, it provides new insights regarding m-banking app adoption in a slightly examined scientific field. Thus, the study intends to assist the banking sector in better understanding their customers with the aim to formulate and apply customized m-business strategies and increase not only the adoption of m-banking apps but also the level of their further use.

Keywords: m-banking apps; behavioral intention; m-banking apps' adoption; UTAUT; ICT inhibitors; ICT facilitators; recommendation

check for updates

Citation: Saprikis, V.; Avlogiaris, G.; Katarachia, A. A Comparative Study of Users versus Non-Users' Behavioral Intention towards M-Banking Apps' Adoption. *Information* **2022**, *13*, 30. https://doi.org/10.3390/info13010030

Academic Editors: Umair Akram, Jiayin Qi and Nada Trunk Širca

Received: 10 December 2021
Accepted: 7 January 2022
Published: 11 January 2022

1. Introduction

The continuous advancement of Information and Communication Technologies (ICT), mainly in the mobile industry with the universal adoption and extensive utilization of mobile devices, has greatly transformed almost every industry sector. Nowadays, the contemporary way of living dictates the intense use of mobile devices, especially smartphones and their numerous applications provided in almost every industry [1]. As a consequence, banking has not been the exception. Banks, as information-intensive enterprises, have been the primary adopters of ICT [1] and virtualized on a considerable scale [2]. They also might be among the very few industries that cover services spanning from offline to mobile channel services [3]. Actually, as they did realize very early the mobile shift of their customers to smartphones and apps [4], they have tried to provide more and more value added self-service functions and enhanced customer experience [5–8]. This shift has significantly changed the way in which their financial and non-financial transactions are conducted via the mobile environment [2,5,9–13]. Furthermore, the high competition between retail banks leads to constant improvements of their m-banking services as customers become gradually even more aware of these services and increasingly more demanding as well [14,15].

M-banking has been developed as a fundamental channel in current years [16]. According to Singh & Srivastava, 2018, m-banking services are regarded as the most value-adding and vital m-commerce apps; thus, banks have invested a lot to m-banking and have considered them as one of their top strategic priorities [17–19]. M-banking services can be accessed via three difference ways: through short message services (SMS banking), mobile Internet and downloadable mobile applications, which is the most popular one [7,8]. M-banking apps, which comprise the aim of this paper and is the newest of the three aforementioned methods, are quite a novel technological innovation with great potential abilities to enhance retail customers' banking experience and modernize banks' operations [20]. In specific, an m-banking app is a software application that banking clients can download and mount on their mobile device that allows them to carry out a variety of banking operations that include, but are not limited to, checking account status, making payments, balance inquiries, transferring funds, making stock investments, receiving critical service alerts, requesting statements, finding ATMs location, messaging personal banking advisors, saving beneficiary information, etc. [21–24]. Additionally, they comprise the main method for modern m-banking [25] and it is predicted to surpass two billion subscribers worldwide by 2030 [26].

M-banking apps offer a wide range of benefits both to retail customers and banks. Specifically, the former can access the banking services without time and geography constraints, thus leading to considerable savings of time [27–31]. As a result, customers can use a wider range of services more often [32]. Furthermore, the vast majority of banking services can be used without customers' commitment to visit any bank branch [12,33–39]. To add to this, m-banking apps have the potential to bring substantial efficiency to traditional client tasks [34] and offer convenience, ease-of-use, security, control, customization, privacy as well as high interactivity [5,23,40–44]. In addition, customers can attain the provided services with a reduced level of financial fees compared to other conventional banking channels [17,45,46], or sometimes, no cost [47]. For example, according to BBC [48], UK users of m-banking can save up to £7bn annually in financial fees by utilizing them. All of the aforementioned benefits can considerably improve individuals' quality of life [34,44,47]. Regarding retail banks, they can increase the efficiency of their services, lower labor and operating costs to a considerable extent, decrease the number of brick-and-mortar bank branches and improve their productivity and finally their revenue [17,30,34,43,46,49,50]. Furthermore, banks can enhance their relationship with their customers by building a new communication channel with them [34,35]. They also have the ability to collect more data concerning users' banking habits, which is a significant asset for targeting and interacting with them more effectively [45,51–53]. Finally, banks can also increase their customer base to rural areas where access is not so easy and pricey [10].

Regardless of the potential advantages of m-banking apps, only a small number of retail clients utilize these services [15,20]. Actually, their global adoption rate is somehow satisfactory (e.g., in the UK nearly half of current bank account holders use m-banking apps) [54], but the usage rate is not as it has been anticipated to be [44]. Specifically, about 44% of individuals worldwide utilize the apps to get informed about their account; however, only 23% of them utilize m-banking apps to conduct transactions [55]. Additionally, even though 53% of individuals use desktop e-banking services to transfer funds, only 24% of them utilize apps for the same operation [56].

Concerning the investigation of the m-banking sector, there have been various research studies which have focused on m-banking services (e.g., [9,10,17,25,40,49,57,58]) aiming at improving the understanding of its acceptance so far, despite the fact that m-banking is still considered to be in the early stages of adoption [57]. However, providing that m-banking apps are quite a recent phenomenon and the newest of the three m-banking methods, studies that focus exclusively on this topic are limited [34]. Therefore, the aim of this empirical research paper is to investigate the determinants that impact individuals on adopting or not exclusively m-banking apps. The study focuses on Greece, which is almost on the bottom of the Digital Economy and Society Index (DESI) 2021 in the European Union [59]. Specifically, Greece is the 25th position out of the 27 countries and is very close to Bulgaria, Romania, Hungary and Poland. Its DESI 2021 score is 37.3, which is far away from the EU's median of 50.7 [59]. Similar to these results, the m-banking penetration rate in Greece is very low as well: less than 10% [41].

The paper examines two groups of individuals, users (adopters) and non-users (non-adopters) of m-banking apps, and aims to reveal if there are differences between the factors that impact them on adopting or not this type of m-banking services. As far as it is concerned, only Veríssimo [60] has compared these two groups of individuals on m-banking app adoption. This paper proposes a comprehensive conceptual model by extending Venkatech's et al. [61] Unified Theory of Acceptance and Use of Technology (UTAUT) with ICT facilitators (i.e., reward and security) and ICT inhibitors (i.e., risk and anxiety), as well as the recommendation factor. Thus, it is the first empirical study that investigates the adopters and non-adopters of m-banking app adoption through a well-established behavioral theory adaption (i.e., UTAUT). This study intends to assist the banking sector and involved entities in better understanding their customers with the aim to formulate and apply customized m-business strategies and increase not only the adoption of m-banking apps but also the level of their further use. The outcome is expected to fill the research gap of the limited investigation of m-banking apps adoption, examine factors that have never been investigated in the field of m-banking apps adoption (i.e., reward, anxiety and recommendation) and reveal important insights both to the academic community, the banking sector and other involved firms and organizations.

The article is comprised of seven sections. Section 2 presents the existing literature review of empirical studies that focus on m-banking apps' adoption. Section 3 provides the proposed conceptual model and the hypotheses of the study. Section 4 presents the research methodology, followed by Section 5, where the data analysis and the study's results are analyzed. Lastly, Section 6 comments on the findings and reveals the theoretical and managerial implications of the examination, along with its limitations and future research directions, whereas in Section 7, the conclusions of the study are provided.

2. Literature Review and Theoretical Background of M-Banking Apps' Adoption

As aforementioned, there have been comparatively a small number of empirical studies that have exclusively examined individuals' behavioral adoption towards m-banking apps. In fact, according to our knowledge, there have been ten studies on this topic. Their presentation is anticipated to provide a better understanding of the subject. Thus, Section 2 focuses on the key characteristics and findings of these studies.

Hew et al. [62] were among the first was among the first researchers who investigated m-banking apps in 2015. Their study was conducted among Malaysian university students and focused on m-banking app adoption intention. In particular, they applied the UTAUT2 model and confirmed that all determinants have a significant positive effect on behavioral ntention (i.e., performance expectancy, effort expectancy, facilitating conditions, habit and hedonic motivation) apart from price value and social influence. Their study focuses on both adopters and non-adopters of m-banking apps. However, they did not investigate the respondents' sample (i.e., adopters and non-adopters) as two separate groups. Veríssimo [60] focused on the enablers and restrictors of m-banking apps. He revealed that adopters' utilization is related to high perceived usefulness, high perceived ease of use, high compatibility and low perceived risk. In contrast, individuals' reluctance to utilize m-banking apps is characterized by low perceived usefulness, low perceived ease of use, low compatibility and high perceived risk. The same year, Alavi & Ahuja [1] examined twelve m-banking apps and segmented customers based on their adoption and utilization of the services offered. Particularly, they proved that perceived ease of use, perceived usefulness, perceived risk and cost and the information necessity from these services and apps that are applied as an alternative option do impact on the adoption and utilization of these apps. Furthermore, they classified adopters to three categories, (a) cognizant indubitables, (b) conservative apprehensives and (c) internet-savvy inquisitives, based on their profile. Likewise, Sampaio et al. [26] targeted on adopters' satisfaction via a cross-cultural study. Their results showed that the provided benefits are positively linked with customers' satisfaction. Furthermore, this satisfaction can strengthen trust, loyalty and positive word-of-mouth towards m-banking apps. On the contrary, Muñoz-Leiva et al. [63] explored non-adopters and proved the positive impact of perceived usefulness, perceived ease of use, perceived trust and social image towards their intention to adopt an m-banking app in Spain.

Poromatikul et al. [16] investigated the factors of continuance intention to m-banking apps adopters in Thailand. Their findings show that satisfaction, trust and expectancy confirmation top the list, followed by perceived risk, image and perceived quality. Thusi & Maduku [20] examined adopters as well. In particular, they studied millennials' adoption and utilization of m-banking apps in South Africa. The researchers extended the UTAUT2 with risk and institution-based trust. The results show that performance expectancy, facilitating conditions, habit, institution-based trust and perceived risk have a statistically significant effect on m-banking apps adoption intention, whereas facilitating conditions, perceived risk and behavioral intention exert a direct effect on apps' utilization. Likewise, Kamdjoug et al. [64] explored the determinants that impact the adopt intention of an m-banking app in Cameroon. Their research model combined the Technology Acceptance Model (TAM), the UTAUT2, the Information System Success Model (ISSM), the Protection Motivation Theory (PMT) and other factors and proved that utilitarian expectation, hedonic motivation, perceived privacy, habit and status gain do have effect on m-banking app adoption intention. Furthermore, the exploitative/explorative utilization of the app impacts on users' loyalty and satisfaction but also has a significant effect on fostering financial inclusion in the country.

Majumdara & Pujari [44] investigated the consumers' acceptance of m-banking apps in the United Arab Emirates. Their study focuses on both adopters and non-adopters of m-banking apps. However, they did not investigate the respondents' sample (i.e., adopters and non-adopters) as two separate groups. The findings showed that perceived usefulness and information availability are the key determinants that impact the acceptance and the level of m-banking apps usage. Finally, Hanif & Lallie [22] examined the influence of cyber security factors to m-banking apps use among individuals aged 55+ in the United Kingdom. In particular, they extended the UTAUT model and proved that performance expectancy, privacy and risk do influence m-banking app utilization. Similar to the Hew et al. [62] and Majumdara & Pujari [44] studies, they did not investigate their sample separately but preferred to jointly analyze the responses.

The extant literature review does reveal that there is a significant research gap on investigating adopters and non-adopters of m-banking apps as separate subgroups. Hence, this article intends to fill this gap and examine their behavioral adoption intention by extending the UTAUT model with reward, security, risk, anxiety and recommendation determinants. Additionally, this study is considered to be the first that investigates the reward, anxiety and recommendation determinants on m-banking app adoption intention. Furthermore, as far as it is concerned, it is the first scientific attempt to investigate this topic in Greece. The paper is also believed to be important due to the fact that the study took place during the COVID-19 pandemic 2nd wave, when individuals were experimenting different ways to perform contactless financial transactions as safe as possible. Consequently, the findings might provide a somehow different perspective towards the adoption and use of this type of m-banking, increase the understanding of the topic and reveal new insights helping both academia and the banking sector develop novel marketing strategies aiming at increasing m-banking apps' acceptance and further use.

3. Proposed Conceptual Model

The proposed conceptual model extends the UTAUT with ICT facilitators (i.e., security and reward) and ICT inhibitors (i.e., risk and anxiety), as well as recommendation factor (Figure 1). This amalgamation of a well-known behavioral theory with two category determinants along with the recommendation factor aims to provide an enhanced understanding of m-banking apps' behavioral intention towards their adoption from individuals. As aforementioned, UTAUT has also been applied and extended by previous researchers on the topic. Specifically, Hanif & Lallie [22] utilized UTAUT, whereas Hew et al. [62], Kamdjoug et al. [64] and Thusi & Maduku [20] applied its updated version (i.e., UTAUT2). Regarding this paper, the original version was preferred instead of the 2nd version, as the "objective of the UTAUT2 model is to pay particular attention to the consumer use context" (Venkatesh et al. [65], p. 158). In contrast, this paper focuses on the adoption stage of m-banking apps. For this reason, it investigates both adopters and non-adopters of this type of m-banking. In the rest of this section, the factors of the proposed model are presented in detail and the research hypotheses are formulated.

3.1. UTAUT Variables

3.1.1. Behavioral Intention

Based on Fishbein & Ajzen's [66] work, behavioral intention is "a person's subjective probability that he/she will perform some behavior". Behavioral intention is the main dependent factor not only to the UTAUT but also to all the basic models, schemes and theories that investigate individuals' behavioral intentions towards the adoption of a technology [67]. Thus, based on Fishbein & Ajzen's [66] definition and Venkatesh et al.'s [61] viewpoint, in this study, the 'behavioral intention' factor describes "an individual's subjective probability that he/she will adopt m-banking apps".

3.1.2. Performance Expectancy

Venkatesh et al. ([65], p. 159) were the first who defined performance expectancy as "the degree to which using a technology will provide benefits to consumers in performing certain activities". In previous m-banking studies, there have been several researchers that proved its positive impact on behavioral intention (e.g., [68–70]). In specific, with regard to m-banking apps, Hew et al. [62], Thusi & Maduku [20] and Hanif & Lallie [22] proved its impact on behavioral intention. Furthermore, performance expectancy is considered as the strongest UTAUT predictor [61] and frequently has the highest impact on users' behavioral intention towards a technological innovation adoption [22,41,68,71]. As a consequence, it is expected that individuals will adopt m-banking apps if they expect to have positive outcomes. Therefore, it is hypothesized that:

Hypothesis 1 (H1). *Performance expectancy has a positive effect on behavioral intention to adopt m-banking apps.*

3.1.3. Effort Expectancy

Effort expectancy is the second major determinant of the UTAUT model and is described as "the degree of ease related with the use of the technology" (Venkatesh et al., [65], p. 159). As a result, the soonest the individual perceives that a technology is easy to use and the interaction with this technology is clear and understandable, the greater the chances are to show an intention to adoption it [41]. In the same way as for performance expectancy, various researchers have examined and confirmed its positive influence to m-banking adoption (e.g., [69,70]). Concerning m-banking apps' adoption investigation, Hew et al. [62], Thusi & Maduku ([20] and Hanif & Lallie [22] proved that effort expectancy positively impacts on behavioral intention. Furthermore, there have been also studies that proved the effect of effort expectancy on performance expectancy not only in the e-commerce field ([71–73]) but also in the context of m-banking apps (e.g., [62]). Thus, it is hypothesized that:

Hypothesis 2 (H2). *Effort expectancy has a positive effect on (a) performance expectancy and (b) behavioral intention to adopt m-banking apps.*

3.1.4. Social Influence

Social influence is defined as "the degree to which an individual perceives that significant others, such as family and friends, believe that he/ she should use a particular technology" (Venkatesh et al. [61], p. 451). Based on their UTAUT model, social influence exerts a positive impact on behavioral intention as well [61]. Concerning empirical studies in m-banking adoption, there have been a significant number of researchers who proved this relationship (e.g., [68,70]). With regard to m-banking apps' adoption, however, despite the fact that previous studies (e.g., [20,62]) examined social influence, they have not revealed a statistically significant association between this factor and behavioral intention. Hence, this paper investigated social influence once again with the aim to prove or not the effect of social influence on behavioral intention. Therefore, it is assumed that:

Hypothesis 3 (H3). *Social influence has a positive effect on behavioral intention to adopt m-banking apps.*

3.1.5. Facilitating Conditions

Facilitating conditions comprise the last determinant of the original UTAUT. Based on its creators, it is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the technology" (Venkatesh et al. [61], p. 453). The original UTAUT model shows that facilitating conditions determinant does not impact positively on behavioral intention. So far, however, there have been a significant number of empirical studies which confirmed the opposite in the context of e-commerce (e.g., [74–76]). With regard to m-banking apps' adoption, as far as it is concerned, only Hew et al. [62] proved its positive effect on behavioral intention. Thus, it is hypothesized that:

Hypothesis 4 (H4). *Facilitating conditions positively influence behavioral intention on adopting m-banking apps.*

3.2. ICT Facilitators

3.2.1. Security

Establishing mechanisms to guarantee the security of users' financial and non-financial transactions, as well as their personal data and information via m-banking apps, is considered a top priority. For this reason, the banking sector has invested a large sum of money and continues to invest for security purposes ([17,26,58]). Khalilzadeh et al. [77] defined perceived security as "the degree to which a customer believes that using a particular m-payment procedure will be secured". Particularly in the pre-adoption stage where individuals do not have any earlier experience, the absence of such actions can definitely prevent them from adopting a novel technology [78]. Likewise, Salisbury et al. [79] expressed that it is vital for individuals to feel secure when they pay mobile, as their worries are reduced. So far, there have been numerous researchers that confirmed the influence of security on users' intention to adopt a technology (e.g., [80–82]). Similarly, Hanif & Lallie [22] proved the influence of security factors in the context of m-banking apps. Therefore, in this study, security refers to "the degree which an individual feels that m-banking apps provide secure mechanisms for protecting their transactions and personal data and information". Hence, it is assumed that the greater the individuals' security perceptions are, the higher their behavioral intention to adopt m-banking apps.

Hypothesis 5 (H5). *Security has a positive effect on behavioral intention to adopt m-banking apps.*

3.2.2. Reward

According to Morgan [83], distinctive competencies are vital determinants for an individual to feel devoted to an enterprise and its products/services. The significant benefits of users when they adopt a mobile technology, such as ubiquity, convenience, high interactivity and personalization, provide great opportunities to banks for luring their customers in several ways. Androulidakis & Androulidakis [84] mentioned that if users are subject to get rewarded when they conduct a transaction via a mobile device, they would be encouraged to use these services more frequently. Up to now, several studies have confirmed the positive effect of reward to the adoption of e-commerce (e.g., [78,82,85]). Hence, if banks enhance their m-banking app functionality with services such as financial incentives, they might have a greater chance of being adopted by their customers. Therefore, it is hypothesized that:

Hypothesis 6 (H6). *Reward positively impacts on behavioral intention to adopt m-banking apps.*

3.3. ICT Inhibitors

3.3.1. Risk

Risk is another key inhibitor in the adoption or not of a technology. Risk can significantly impact individuals not only to the extent of the utilization of a technological innovation but also to the first step: the initial adoption. As a consequence, it is regarded as an expected and undesirable situation [86]. The importance of risk to the adoption of an m-commerce service has forced many researchers to examine and finally prove its negative impact (e.g., [87–89]). Regarding m-banking apps' adoption, a significant number of studies have also revealed its negative effect [1,16,20,22,60]. Moreover, Corbitt et al. [90] mentioned that there should be a connection between risk and anxiety, as individuals' anxiety in conducting online purchases can be minimized if the perceived risk levels are as low as possible. As a result, Saprikis & Avlogiaris [73,78] proved the strong positive effect of risk on anxiety. Hence, it is assumed that:

Hypothesis 7 (H7). *Risk has (a) a negative effect on behavioral intention to adopt m-banking apps and (b) a positive effect on anxiety.*

3.3.2. Anxiety

Anxiety is regarded as a key inhibitor to a technological innovation adoption. According to Igbaria & Iivari [91], anxiety is a condition where users feel uncomfortable, nervous and/or aversive at the prospect of utilizing a technology. Despite the fact that anxiety has been greatly examined from a large number of researchers in the context of m-commerce adoption and its negative effect on behavioral intention has been proved (e.g., [82,92]), there are no empirical studies that examined this highly critical determinant on m-banking apps. Hence, it is anticipated that the more anxious users are towards m-banking apps, the less possible is to adopt their provided m-services. It should be mentioned, though, that mobile device users may express higher levels of perceived anxiety compared to traditional transactions or e-transactions because of the lack of geographical and time-based limitations [93,94].

Hypothesis 8 (H8). *Anxiety exerts a negative effect on behavioral intention to adopt m-banking apps.*

3.4. Recommendation

According to Leong et al. [95], when consumers have higher behavioral intention towards a technological innovation, they are more likely to become adopters. Based on this statement, Oliveira et al. [81] proved that individuals' behavioral intention to adopt m-payment positively influences their behavioral intention to recommend m-payment technologies to others. Hence, based on the scope of this paper, it is assumed that:

Hypothesis 9 (H9). *Behavioral intention to adopt m-banking apps exerts a positive effect on behavioral intention to recommend m-banking apps to others.*

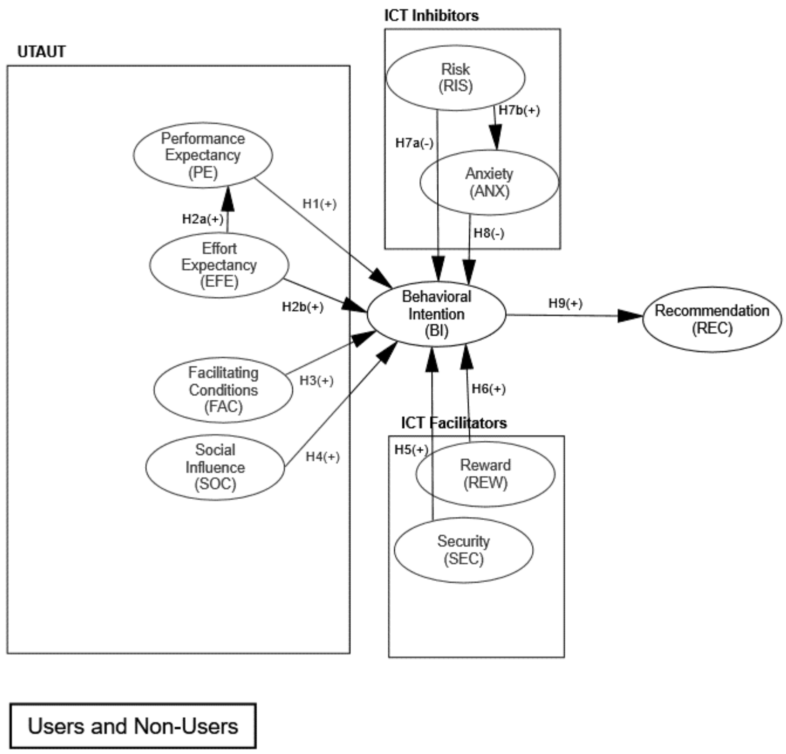

Figure 1. Hypothesized conceptual model.

4. Research Methodology

Section 4 presents the applied research methodology of the study. The procedure of data collection and the demographic characteristics of the final sample are analyzed as well.

4.1. Measurement Instrument

With the intention of examining the factors of the aforementioned proposed conceptual model (Figure 1), a questionnaire was preferred as the most suitable method for the collection of the data required. Therefore, the questionnaire developed was greatly based on the existing literature review for validity and reliability purposes. Particularly, the fundamental items for investigating UTAUT determinants (i.e., performance expectancy, effort expectancy, facilitating conditions, social influence and behavioral intention) were adapted from the developers of the UTAUT [61]. With regard to ICT facilitators (i.e., reward and security), the research papers of Salisbury et al. [79], Saprikis et al. [82] and Zarmpou et al. [85] were adapted. Concerning the ICT inhibitors (i.e., risk and anxiety), the measurement items of this study were based on Compeau et al. [70], Jarvenpaa et al. [96], Thatcher & Perrewe [97], Venkatesh & Bala [98] and Wakefield & Whitten's [99] research works. Moreover, the recommendation determinant was adapted from Oliveira et al.'s [81] empirical study. At this point, it should be highlighted that a five-point Likert scale was applied to all measurement items. Table 1 presents in detail the items of the constructs of the proposed conceptual model. Finally, five demographic questions (i.e., sex, age, place of residence, occupation and education) were included in the questionnaire as well.

The measurement instrument was first drafted in English. Afterwards, a university English professor translated it to the Greek language aiming at guaranteeing its consistency. Then, it was pre-tested from two academicians and a group of 15 respondents to reveal possible clarity and accuracy issues. This pilot test did reveal that the questionnaire items and scales were reliable and valid.

Table 1. Questionnaire of the study.

Research Variables	Measurement Items	Sources
Performance Expectancy (PE)	PE1: I think that using an m-banking app through my smartphone would help me accomplish my transactions more quickly	[61]
	PE2: I think that using an m-banking app through my smartphone would increase my chances of completing transactions that are important to me	
Effort Expectancy (EFE)	EFE1: I think it would be easy for me to learn how to use an m-banking app through my smartphone	
	EFE2: I think that it would be easy for me to use an m-banking app through my smartphone	
	EFE3: I think that my interactions via an m-banking app through my smartphone would be clear and understandable	
Social Influence (SOC)	SOC1: People who influence my behavior think that I should use an m-banking app through my smartphone	
	SOC2: People who are important to me think that I should use an m-banking app through my smartphone	
	SOC3: People whose opinion count think that I should use an m-banking app through my smartphone	
Facilitating Conditions (FAC)	FAC1: I think that I have the proper smartphone to use an m-banking app	
	FAC2: I think that I could use an m-banking app with my current smartphone	
Behavioral Intention (BI)	BI1: I intend to use an m-banking app through my smartphone in the near future	
	BI2: I predict I would use an m-banking app through my smartphone in the near future	
	BI3: If I have the chance I would use an m-banking app through my smartphone	
Reward (REW)	REW1: I would use an m-banking app through my smartphone if it provides motives	[82,85]
	REW2: I would use an m-banking app through my smartphone if it provides information on special offers	
Security (SEC)	SEC1: I think using an m-banking app through my smartphone is secure to send and receive data/ information	[79]
	SEC2: I feel secure to use an m-banking app through my smartphone	
	SEC3: I would feel safe to provide sensitive information about myself via an m-banking app through my smartphone	
RISK (RIS)	RIS1: I think that there would be a high potential for financial fraud if I use an m-banking app through my smartphone	[96,99]
	RIS2: I think that other people could know information about my transactions if I use an m-banking app through my smartphone	
	RIS3: I think that using an m-banking app through my smartphone would be risky	
Anxiety (ANX)	ANX1: I would feel apprehensive about using an m-banking app through my smartphone	[70,97,98]
	ANX2: Using an m-banking app through my smartphone would make me feel nervous	
	ANX3: Using an m-banking app through my smartphone would make me feel uncomfortable	
Recommendation (REC)	REC1: If I have a good experience with an m-banking app through my smartphone, I will recommend it to friends and relatives	[81]
	REC2: I intend to recommend to friends and relatives to use an m-banking app through their smartphone	
	REC3: I think that I would recommend to friends and relatives to use an m-banking app through their smartphone	

4.2. Data Collection and Sample Characteristics

To gather the data for testing the hypothesized conceptual model, the questionnaire of the study was distributed online to email accounts and social media for a two month period (December 2020–January 2021). Convenience sampling was applied because the size of the total population was unknown. However, before its distribution, the questionnaire was pre-tested to a sample of 37 mobile users. The pilot test report showed that the items were valid and reliable and that these responses were excluded from the final sample of the investigation to avoid results' skewing.

A total of 837 smartphone users in Greece responded and comprised the sample of the study. Table 2 depicts sample's demographic characteristics. The results reveal that there were more female respondents (55.2%) than male respondents (44.8%). The majority of them were aged between 25 and 44 years old (63.7%) and mainly worked as private employees (38.6%), public servants (19.8%) or freelancers (18.9%). With regard to their education level, about half of them (51.8%) graduated from a university/college, whereas 23.4% of them hold a postgraduate degree or just completed high school (24.4%).

Table 2. Demographic characteristics.

Demographics	**Respondents (N)**	**%**
	Sex:	
Male	375	44.8
Female	462	55.2
	Age:	
18–24	124	14.8
25–34	302	36.1
35–44	231	27.6
45–54	177	21.1
>54	3	0.4
	Occupation:	
Public servant	166	19.8
Private employee	323	38.6
Freelancer	158	18.9
Unemployed	105	12.5
other	85	10.2
	Education:	
Elementary School	3	0.4
High school	204	24.4
University/College	434	51.8
Master/Phd	196	23.4
	Monthly salary:	
<600 €	179	21.4
601–900 €	171	20.4
901–1200 €	163	19.5
1201–1500 €	90	10.8
1501–1800 €	40	4.8
1801–2500 €	22	2.6
>2500 €	24	2.9
Not answer	148	17.7

5. Data Analysis and Results

This section is divided in two parts. Part I comprises the measurement model results. Specifically, the reliability analysis of the measurement items, as well as the convergent and discriminant validity between the latent constructs, are presented. The model's overall goodness-of-fit indexes are also analyzed. Part II presents the structural model of the research hypotheses of both m-banking app users and non-users in two separate analyses.

5.1. Measurement Model

First, Cronbach's alpha test was utilized to measure the reliability of the items of the questionnaire. The results surpassed the 0.7 threshold (0.845–0.962 range) [100] (Table 3). Second, convergent and discriminant validity were measured via factors' loading indicators. All of them exceeded the 0.4 threshold (0.685–0.920 range) [101]. Third, regarding the Composite Reliability (CR) value, it surpassed the 0.6 in all cases (0.735–0.924) [102] and the Average Variance Extracted (AVE) of each construct was above the 0.5 threshold (0.57–0.845) [103]. In addition to these, the possible relationships between constructs with the square roots of AVE values were also compared. The results depict that the square roots of AVE values were greater than the inter-construct correlations [103] (Table 4). Hence, the results mentioned below indicate that both convergent and discriminant validity were maintained.

Table 3. Standardized factor loadings and individual item reliability.

Construct	Item	Loading	CR	AVE	Cronbach's α
Performance Expectancy (PE)	PE1	0.740	0.735	0.581	0.845
	PE2	0.784			
Effort Expectancy (EFE)	EFE1	0.814	0.852	0.658	0.893
	EFE2	0.803			
	EFE3	0.816			
Facilitating Conditions (FAC)	FAC1	0.866	0.838	0.722	0.904
	FAC2	0.833			
Social Influence (SOC)	SOC1	0.876	0.924	0.801	0.903
	SOC2	0.920			
	SOC3	0.889			
Security (SEC)	SEC1	0.769	0.798	0.570	0.920
	SEC2	0.749			
	SEC3	0.745			
Reward (REW)	REW1	0.919	0.916	0.845	0.962
	REW2	0.920			
Anxiety (ANX)	ANX1	0.832	0.871	0.692	0.916
	ANX2	0.838			
	ANX3	0.826			
Risk (RIS)	RIS1	0.795	0.800	0.571	0.896
	RIS2	0.783			
	RIS3	0.685			
Behavioral Intention (BI)	BI1	0.824	0.843	0.642	0.948
	BI2	0.811			
	BI3	0.768			
Recommendation (REC)	REC1	0.782	0.848	0.650	0.937
	REC2	0.818			
	REC3	0.818			
		Total Variance Explained = 87.550			

Table 4. Inter-correlation and square roots of AVE.

	PE	EFE	SOC	FAC	SEC	REW	ANX	RIS	BI	REC
PE	0.76									
EFE	0.67	0.81								
SOC	0.18	0.10	0.85							
FAC	0.55	0.67	0.13	0.89						
SEC	0.45	0.41	0.19	0.42	0.75					
REW	0.22	0.14	0.28	0.25	0.29	0.92				
ANX	−0.36	−0.49	0.08	−0.46	−0.42	−0.10	0.83			
RIS	−0.34	−0.42	0.01	−0.38	−0.66	−0.11	0.72	0.75		
BI	0.48	0.47	0.14	0.53	0.47	0.23	−0.41	−0.37	0.80	
REC	0.43	0.36	0.28	0.39	0.48	0.29	−0.31	−0.39	0.50	0.81

Furthermore, Confirmatory Factor Analysis (CFA) was applied. The model's overall goodness-of-fit was evaluated through several measures. These measures and recommended values are depicted in Table 5. Thus, a sufficiently fitted model should have a chi-square/df ratio less than 5 [104]; the goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), normed fit index (NFI), incremental fit index (IFI) and Tucker-Lewis index (TLI) values should be greater than 0.90 [105]; and a root mean square error of approximation (RMSEA) should be less than 0.05 [106]. Based on the CFA results, the measurement model illustrated in Figure 1 was appropriate because all indicators of the model are satisfactory according to the recommended values of the literature (Table 5).

Table 5. Evaluation of model goodness-of-fit.

Measures	Recommended Value	Measurement Model
χ^2/df	≤5.00	1.709
Goodness of fit index (GFI)	≥0.90	0.949
Adjusted goodness of fit index (AGFI)	≥0.90	0.930
Comparative fit index (CFI)	≥0.90	0.985
Normed fit index (NFI)	≥0.90	0.965
Incremental fit index (IFI)	≥0.90	0.985
Tucker-Lewis index (TLI)	≥0.90	0.981
Root mean square Error of Approximation (RMSEA) [90%CI]	≤0.05	0.034 [0.028–0.039]

5.2. Structural Models

Structural Equation Modeling (SEM) was first performed to examine the hypotheses of the proposed conceptual model on m-banking app users. SEM was applied through the utilization of the IBM SPSS Amos version 24 software. The results revealed a good model fit (Table 6). Specifically, all goodness-of-fit measures were in accordance with the suggested thresholds [104–107].

Table 6. Evaluation of model goodness-of-fit—Users.

Measures	Recommended Value	Structural Model
χ^2/df	≤5.00	1.793
Goodness of fit index (GFI)	≥0.90	0.944
Adjusted goodness of fit index (AGFI)	≥0.90	0.926
Comparative fit index (CFI)	≥0.90	0.982
Normed fit index (NFI)	≥0.90	0.961
Incremental fit index (IFI)	≥0.90	0.982
Tucker-Lewis index (TLI)	≥0.90	0.978
Root mean square Error of Approximation (RMSEA) [90%CI]	≤0.05	0.036 [0.031–0.040]

The significance of the research hypotheses is presented in Table 7 and is also depicted graphically in Figure 2. Nine out of the eleven hypotheses were verified. The exclusions are the effect of effort expectancy and risk on the behavioral intention. Thus, H2b and H7a are not supported. In contrast, performance expectancy exerts a positive effect on behavioral intention (β = 0.20, $p < 0.001$), effort expectancy greatly impacts on performance expectancy (β = 0.68, $p < 0.001$) and facilitating condition construct indicates a positive impact on behavioral intention (β = 0.21, $p < 0.001$). Hence, hypotheses H1, H2a and H3 are confirmed. Moreover, social influence also exerts a positive effect on behavioral intention (β = 0.09, $p < 0.01$); thus, H4 is also verified.

Table 7. Path coefficients—Users. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Hypotheses	Paths	Coefficients
H1	PE→BI	0.20 ***
H2	(a) EFE→PE (b) EFE→BI	(a) 0.68 *** (b) Non-Significant
H3	FAC→BI	0.21 ***
H4	SOC→BI	0.09 **
H5	SEC→BI	0.26 ***
H6	REW→BI	0.07 *
H7	(a) RIS→BI (b) RIS→ANX	(a) Non-Significant (b) 0.76 ***
H8	ANX→BI	−0.20 ***
H9	BI→REC	0.92 ***

Concerning ICT facilitators, both security (β = 0.26, $p < 0.001$) and reward (β = 0.07, $p < 0.05$) factors positively impact on behavioral intention. As a result, hypotheses H5 and H6 are verified. With regard to ICT inhibitors, risk is greatly connected with anxiety (β = 0.76, $p < 0.001$). Anxiety also exerts a negative statistically significant effect on behavioral intention (β = −0.20, $p < 0.001$). Hence, H7b and H8 are confirmed. Finally, behavioral intention is greatly linked with recommendation (β = 0.92, $p < 0.001$) (H9).

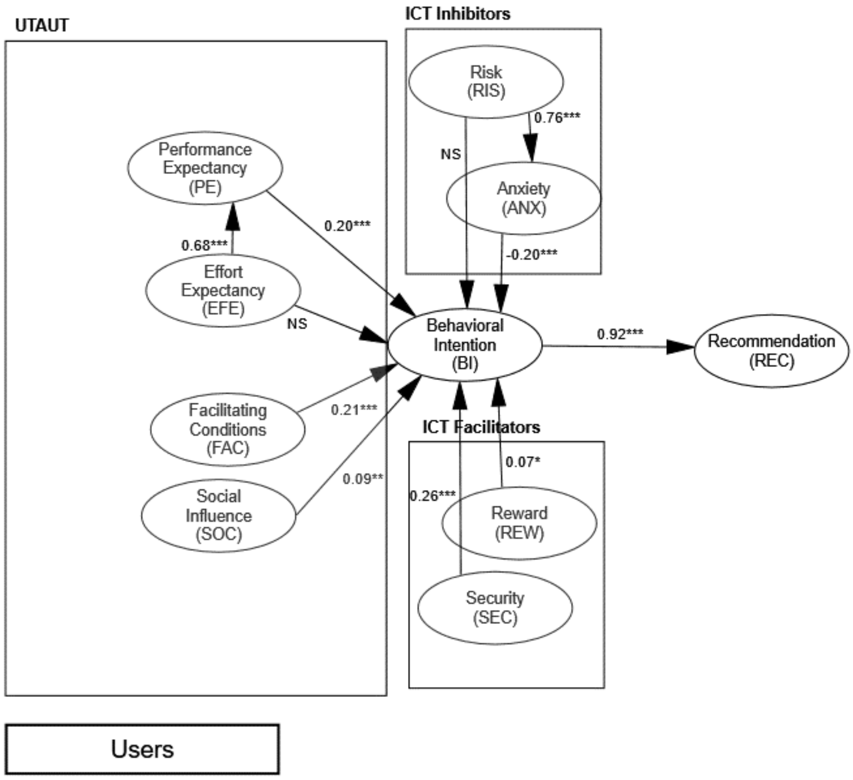

Figure 2. Validated conceptual model—Users. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, NS: Non-Significant.

Structural Equation Modeling (SEM) was then performed to examine the hypotheses of the proposed conceptual model on m-banking app non-users. The results of this subgroup of the sample revealed a good model fit as well (Table 8). In particular, all goodness-of-fit measures were also above or very close to the suggested thresholds [104–107].

Table 8. Evaluation of model goodness-of-fit—Non-users.

Measures	Recommended Value	Structural Model
χ^2/df	$\leq$5.00	1.488
Goodness of fit index (GFI)	$\geq$0.90	0.869
Adjusted goodness of fit index (AGFI)	$\geq$0.90	0.834
Comparative fit index (CFI)	$\geq$0.90	0.972
Normed fit index (NFI)	$\geq$0.90	0.920
Incremental fit index (IFI)	$\geq$0.90	0.972
Tucker-Lewis index (TLI)	$\geq$0.90	0.967
Root mean square Error of Approximation (RMSEA) [90%CI]	$\leq$0.05	0.048 [0.039–0.058]

The results of the hypotheses examination are presented in Table 9 and depicted in Figure 3. Seven out of the eleven hypotheses were confirmed. The exclusions are the impact of effort expectancy, facilitating conditions, security and anxiety on behavioral intention. Thus, H2b, H3, H5 and H8 are not supported. In contrast, performance expectancy has a strong, positive impact on behavioral intention (β = 0.43, $p < 0.001$). Furthermore, effort expectancy positively impacts on performance expectancy (β = 0.58, $p < 0.001$) and social influence also has a positive effect on behavioral intention (β = 0.13, $p < 0.05$). Therefore, hypotheses H1, H2a and H4 are all verified.

Table 9. Path coefficients—Non-users. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Hypotheses	Paths	Coefficients
H1	PE→BI	0.43 ***
H2	(a) EFE→PE (b) EFE→BI	(a) 0.58 *** (b) Non-Significant
H3	FAC→EFE	Non-Significant
H4	SOC→BI	0.13 *
H5	SEC→BI	Non-Significant
H6	REW→BI	0.28 ***
H7	(a) RIS→B1 (b) RIS→ANX	(a) −0.26 * (b) 0.70 ***
H8	ANX→BI	Non-Significant
H9	BI→ REC	0.99 ***

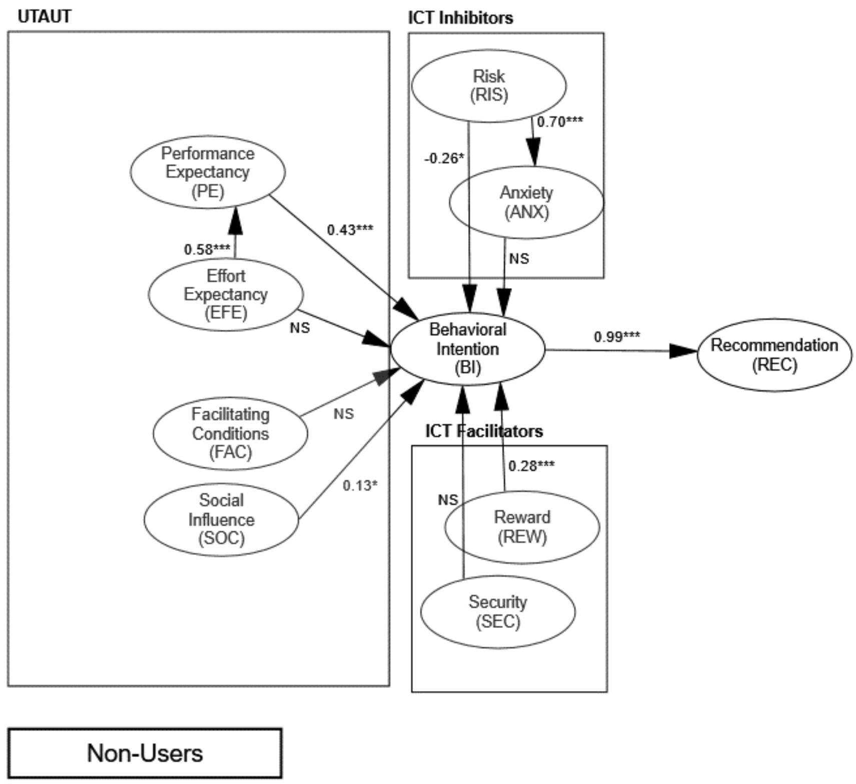

Figure 3. Validated conceptual model—Non-Users. $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, NS: Non-Significant.

Concerning ICT facilitators, only reward (β = 0.28, $p < 0.05$) exerts a positive effect on behavioral intention. As a result, H6 is verified. With regard to ICT inhibitors, risk exerts a negative impact on behavioral intention (β = −0.26, $p < 0.05$) and is greatly associated with anxiety (β = 0.70, $p < 0.001$). Thus, both H7a and H7b are confirmed. Finally, behavioral intention is greatly linked with recommendation (β = 0.99, $p < 0.001$) (H9).

6. Discussion

This study aims to develop a comprehensive model and compare the impact of UTAUT determinants, along with fundamental ICT inhibitors and facilitators as well as recommendation factor on users (adopters) and non-users' (non-adopters) adoption of m-banking apps in a holistic perspective. The findings reveal useful information regarding the behavioral intention of both examined groups of respondents. To be more specific, regarding UTAUT factors, both structural models depict the statistical significance of performance expectancy to behavioral intention. These findings are in accordance with prior studies on the topic [20,22,62]. This factor, however, revealed a stronger effect on non-users compared to users. Therefore, it might be alleged that this group of respondents, despite the fact that they do not currently utilize m-banking app services, perceive that their potential adoption would greatly benefit them to accomplish m-banking transactions more quickly and in a more efficient way. Additionally, both structural models reveal that social influence has a statistically positive impact on behavioral intention. It should be emphasized, though, that in spite of the fact that several researchers have proved this relationship in the broad m-banking adoption field (e.g., [68,70]), this is the first study where this hypothesis has been confirmed in the context of m-banking app adoption. Hew et al. [62] and Thusi & Maduku [20], who also investigated this relationship in their empirical studies, did not confirm it. Concerning effort expectancy, both respondents' groups proved its insignificance. However, effort expectancy revealed an indirect effect to behavioral intention via performance expectancy in both structural models. This relationship has also been proved in previous studies not only in the e-commerce field (e.g., [71–73]) but also in the context of m-banking apps [62]. With regard to facilitating conditions factor, its impact on behavioral intention was confirmed only to users' structural model. As far as it is concerned, this is the second empirical investigation after Hew et al. [62] work where this factor has been proved towards behavioral intention. This might be attributed to the fact that non-users have not experimented with m-banking apps up to now; thus, they are unaware if their smartphone fully complies with the requirements of these applications. At this point, it should be mentioned that the rejection of basic factors (i.e., effort expectancy and facilitating conditions) from a well-known behavioral theory model, such as UTAUT, is normal when the original model is enhanced with additional determinants, because such an approach can greatly modify the constructs' dynamics (e.g., [73,81]).

Concerning ICT inhibitors, differences between users and non-users were revealed. In specific, risk was confirmed to exert a negative impact on behavioral intention only to non-users. This is normal, as this group of respondents is not familiar with m-banking app services. Therefore, their reluctance may be attributed to their perceptions that these transactions are risky, can be intruded by others and/or have a high potential for financial fraud. The confirmation of risk is in accordance with prior studies' results in the context of m-banking apps (i.e., [1,16,20,22,60]). Following Corbitt et al.'s [94] allegation that there should be a connection between risk and anxiety, however, this study confirmed this relation to both groups of respondents. This relation has been also proved from Saprikis & Avlogiaris' [73,78] studies in the broad context of m-commerce. According to our knowledge, this is the first empirical study where this relationship has been confirmed in the m-banking apps field. With regard to anxiety, it was confirmed that it has a negative effect on behavioral intention only to users. This may be attributed to the fact that this group of individuals utilize these services and therefore feel apprehensive and nervous for fear of making something wrong through the transaction procedure. On the other hand, non-users are inexperienced towards m-banking app utilization; thus, they do not feel anxious about it at the moment. The confirmation of such a highly critical determinant is also examined and confirmed for the first time in the context of m-banking apps.

Concerning ICT facilitators, reward was confirmed to have a statistically significant impact on behavioral intention to both groups. However, non-users mentioned that this factor is much more important to them compared to users. Similar to anxiety, as far as it is concerned, this determinant has never been examined and confirmed before in the context of m-banking apps. With regard to security, its positive impact on behavioral intention was proved only to users. This might be attributed to the fact that their actual involvement with m-banking apps reveals no security issues to them; thus, they feel secure to provide and receive sensitive information through such apps. On the contrary, non-users' inexperience makes them reluctant to feel secure towards m-banking apps. Similarly, Hanif & Lallie [22] were the first and only researchers who proved the impact of security in the context of m-banking apps.

Finally, the recommendation factor was proved to be highly impacted by behavioral intention to both examined groups. This result is very interesting and reveals the positive attitude not only to users but also to non-users regarding their future intentions towards m-banking apps adoption. Hence, the satisfied m-banking app customer can greatly force others, such as friends and relatives, towards m-banking app adoption. The statistical significance of non-users is quite surprising, as they have not utilized these apps yet; however, the results of this empirical study show their positive intentions to use these m-services in the very near future. Oliveira et al. [81] proved this relationship in the context of m-payments; however, this is the first study where it is confirmed in the context of m-banking.

6.1. Theoretical and Practical Implications

The findings of this empirical examination are expected to contribute in various aspects in the context of m-banking apps' adoption in the academia. First, the study helps the extant literature, as it develops and confirms a novel theoretical and conceptual model. In particular, on this model, as far as it is concerned, a number of determinants have been examined and proved for the first time. These research confirmations are the impact of social influence, reward and anxiety factors on behavioral intention, the relationship between risk and anxiety and the impact of behavioral intention to recommendation. As a result, the study provides new insights regarding m-banking app adoption in a slightly examined scientific field (i.e., there have been only ten empirical studies that focus only on this topic). Second, the fact that it took place during the 2nd wave of COVID-19 pandemic strengthens the importance of its findings, as individuals are more receptive to m-services with the aim to avoid face-to-face interactions for safety concerns along with the intense digital transformation of various industry sectors, not to mention the banking sector. Third, the conceptual model of this paper could be utilized as a useful tool from the academic community, which investigates m-banking apps' adoption and m-banking in general. For example, the confirmation or not of the factors of this model in other countries with similar cultural and socio-demographic characteristics might increase the effect of this study. Forth, additional factors could be adjusted to it with the aim of investigating alternative determinants that might impact on individuals' behavioral intention towards the adoption and further use of m-banking apps or other m-banking behavioral issues. To sum up, it is expected that this study offers a comprehensive approach of m-banking apps' adoption via the suggested model and its results to the academia.

The findings of the study are expected to be important to the banking sector as well. The confirmation or not of the factors of this conceptual model could definitely help banks customize their strategic policies in the digital era, especially in the context of the m-services, which are provided via apps. For instance, it is really promising that both group of respondents, even non-adopters, expressed their intention to recommend m-banking apps to friends and relatives. It goes without saying that it is vital for decision-makers in the retail banking sector to have valuable information with the aim of better detecting and comprehending the influential parameters that impact individuals' adoption of m-banking apps. Furthermore, the different impact of the factors examined to the two groups of respondents (i.e., users versus non-users) could significantly support managers follow different marketing and promotion practices on these groups. For example, managers can be assisted in their alternative practices provided with the aim to boost current users' level of m-banking app utilization. On the other hand, they can be helped in their efforts to attract clients who do not current utilize m-banking app services and try to transfer them from their branches to the online environment. According to the findings of this study, as was previously mentioned, non-users seem very positive to adopt these apps. For instance, the significant effect of reward to them can be greatly utilized from banks to lure non-users towards apps' adoption. Financial motives, credits' acquisition for m-banking app transactions and similar actions should be greatly considered. To add to this, advertising campaigns towards the minimization of their security doubts should be applied as well. These activities might reduce the perceived risk that non-users also have. As was already mentioned in the introduction section, this transfer will greatly help both banking and customers (win-win situation). On the contrary, it is of high importance to minimize the perceived anxiety of current users towards m-banking app utilization. Therefore, banks need to further explore why adopters feel anxious when they use an m-banking app and apply analogous deterrent actions. For instance, an even more user-friendly app interface may reduce individuals' anxiety issues. In conclusion, the results of this study are considered as a vital assistance for banks in a period where the whole sector in the vast majority of countries has already started its complete transformation to the digital area.

6.2. Limitations and Further Research

Despite the fact that the study offers useful insights, there are a number of limitations which need to be mentioned. Some of them can lead to further research examination. First, as was already mentioned in the research methodology section, convenience sampling was applied. Thus, the results cannot be generalized for the whole population in Greece. On the other hand, a more meticulous sample section can be addressed with the aim of generalizing on the results. Second, a cross-cultural examination of the proposed conceptual model is expected to reveal even more vital information about m-banking apps' adoption. Taking into consideration that these m-services are globally utilized, such a procedure would definitely enhance the quality of the study. Third, the proposed conceptual model might be improved with additional determinants aiming at providing a more enhanced research framework that may offer a more holistic research approach of the topic.

7. Conclusions

To sum up, mobile devices along with their numerous apps provided have prevailed in the digital environment and comprise the main portal to the internet for the main online users globally. Therefore, almost all industry sectors have already tried to benefit from these technological innovations. Banks, as information-intensive firms, have been major adopters of ICT [1]. As they did realize very early the mobile shift of their customers to smartphones and apps [4], they have tried to provide more and more value added self-service functions and enhanced customer experience [6–8,24]. Hence, m-banking has been developed as a fundamental channel in current years [16] and its services are regarded as the most value-adding and vital m-commerce apps [108]. Thus, this study aims to investigate a slightly examined topic and comprise the first empirical paper that investigates users and non-users of m-banking app adoption through the adaption of the UTAUT model. Moreover, it examines and confirms the significance of a number of factors that have never been investigated before in the field of m-banking apps' adoption. Furthermore, the examination of users versus non-users reveals both similarities and differences between these two groups. This information is considered as vital for the banking sector. The paper is also believed to be important due to the fact that the study took place during COVID-19 pandemic 2nd wave, when individuals were experimenting with different ways to perform contactless financial transactions as safe as possible. Consequently, the findings might provide a somehow different perspective towards the adoption and use of this type of m-banking, increase the understanding of the topic and reveal new insights helping both academia and the banking sector to develop novel marketing strategies aiming at increasing m-banking apps' acceptance and level of utilization.

Author Contributions: Conceptualization, V.S.; methodology, V.S. and G.A.; software, V.S. and G.A.; validation, V.S. and G.A.; formal analysis, V.S.; investigation, V.S. and A.K.; resources, V.S. and G.A.; data curation, G.A.; writing—original draft preparation, V.S.; writing—review and editing, V.S. and G.A.; visualization, G.A.; supervision, V.S.; project administration, V.S.; funding acquisition, No one. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Please refer to suggested Data Availability Statements at 10.6084/m9.figshare.18160715.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Alavi, S.; Ahuja, V. An Empirical Segmentation of Users of Mobile Banking Apps. *J. Internet Commer.* **2016**, *15*, 390–407. [CrossRef]
2. Bons, R.W.H.; Alt, R.; Lee, H.G.; Weber, B. Banking in the Internet and mobile era. *Electron. Mark.* **2012**, *22*, 197–202. [CrossRef]
3. Souiden, N.; Ladhari, R.; Chaouali, W. Mobile banking adoption: A systematic review. *Int. J. Bank Mark.* **2020**, *39*, 214–241. [CrossRef]
4. Zhang, T.; Lu, C.; Kizildag, M. Banking "on-the-go": Examining consumers' adoption of mobile banking ser-vices. *Int. J. Qual. Serv. Sci.* **2018**, *10*, 279–295.
5. Laukkanen, T. Consumer adoption versus rejection decisions in seemingly similar service innovations: The case of the Internet and mobile banking. *J. Bus. Res.* **2016**, *69*, 2432–2439. [CrossRef]
6. Martins, C.; Oliveira, T.; Popovič, A. Understanding the Internet banking adoption: A unified theory of ac-ceptance and use of technology and perceived risk application. *Int. J. Inf. Manag.* **2014**, *34*, 1–13. [CrossRef]
7. Shankar, A.; Jebarajakirthy, C.; Ashaduzzaman, M. How do electronic word of mouth practices contribute to mobile banking adoption? *J. Retail. Consum. Serv.* **2020**, *52*, 101920. [CrossRef]
8. Shankar, A.; Datta, B.; Jebarajakirthy, C.; Mukherjee, S. Exploring Mobile Banking Service Quality: A Qualitative Approach. *Serv. Mark. Q.* **2020**, *41*, 182–204. [CrossRef]
9. Bhatiasevi, V. An extended UTAUT model to explain the adoption of mobile banking. *Inf. Dev.* **2016**, *32*, 799–814. [CrossRef]
10. Ha, K.-H.; Canedoli, A.; Baur, A.W.; Bick, M. Mobile banking—Insights on its increasing relevance and most common drivers of adoption. *Electron. Mark.* **2012**, *22*, 217–227. [CrossRef]
11. Lee, K.C.; Chung, N. Understanding factors affecting trust in and satisfaction with mobile banking in Korea: A modified DeLone and McLean's model perspective. *Interact. Comput.* **2009**, *21*, 385–392. [CrossRef]
12. Oliveira, T.; Faria, M.; Thomas, M.A.; Popovič, A. Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *Int. J. Inf. Manag.* **2014**, *34*, 689–703. [CrossRef]
13. Sharma, S.K. Integrating cognitive antecedents into TAM to explain mobile banking behavioral intention: A SEM-neural network modeling. *Inf. Syst. Front.* **2017**, *21*, 815–827. [CrossRef]
14. Komulainen, H.; Saraniemi, S. Customer centricity in mobile banking: A customer experience perspec-tive. *Int. J. Bank Mark.* **2019**, *37*, 1082–1102. [CrossRef]
15. Shaikh, A.A.; Karjaluoto, H. Mobile banking adoption: A literature review. *Telemat. Inform.* **2015**, *32*, 129–142. [CrossRef]
16. Poromatikul, C.; De Maeyer, P.; Leelapanyalert, K.; Zaby, S. Drivers of continuance intention with mobile banking apps. *Int. J. Bank Mark.* **2019**, *38*, 242–262. [CrossRef]
17. Baabdullah, A.M.; Alalwan, A.A.; Rana, N.P.; Kizgin, H.; Patil, P. Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model. *Int. J. Inf. Manag.* **2018**, *44*, 38–52. [CrossRef]
18. Giovanis, A.; Athanasopoulou, P.; Assimakopoulos, C.; Sarmaniotis, C. Adoption of mobile banking services: A comparative analysis of four competing theoretical models. *Int. J. Bank Mark.* **2019**, *37*, 1165–1189. [CrossRef]
19. Luarn, P.; Lin, H.-H. Toward an understanding of the behavioral intention to use mobile banking. *Comput. Hum. Behav.* **2005**, *21*, 873–891. [CrossRef]
20. Thusi, P.; Maduku, D.K. South African millennials' acceptance and use of retail mobile banking apps: An inte-grated perspective. *Comput. Hum. Behav.* **2020**, *111*, 106405. [CrossRef]
21. Gu, J.-C.; Lee, S.-C.; Suh, Y.-H. Determinants of behavioral intention to mobile banking. *Expert Syst. Appl.* **2009**, *36*, 11605–11616. [CrossRef]
22. Hanif, Y.; Lallie, H.S. Security factors on the intention to use mobile banking applications in the UK older gen-eration (55+). A mixed-method study using modified UTAUT and MTAM-with perceived cyber security, risk, and trust. *Technol. Soc.* **2021**, *67*, 101693. [CrossRef]
23. Karjaluoto, H.; Shaikh, A.A.; Saarijärvi, H.; Saraniemi, S. How perceived value drives the use of mobile finan-cial services apps. *Int. J. Inf. Manag.* **2019**, *47*, 252–261. [CrossRef]
24. Laukkanen, T. Internet vs mobile banking: Comparing customer value perceptions. *Bus. Process. Manag. J.* **2007**, *13*, 788–797. [CrossRef]
25. Farah, M.; Hasni, M.J.S.; Abbas, A.K. Mobile-banking adoption: Empirical evidence from the banking sector in Pakistan. *Int. J. Bank Mark.* **2018**, *36*, 1386–1413. [CrossRef]
26. Sampaio, C.H.; Ladeira, W.J.; Santini, F.D.O. Apps for mobile banking and customer satisfaction: A cross-cultural study. *Int. J. Bank Mark.* **2017**, *35*, 1133–1153. [CrossRef]

27. Hogan, J.E.; Lemon, K.N.; Libai, B. Quantifying the ripple: Word-of-mouth and advertising effective-ness. *J. Advert. Res.* **2004**, *44*, 271–280. [CrossRef]
28. Goyette, I.; Ricard, L.; Bergeron, J.; Marticotte, F. e-WOM Scale: Word-of-mouth measurement scale for e-services context. *Can. J. Adm. Sci./Rev. Can. Des Sci. L'administration* **2010**, *27*, 5–23. [CrossRef]
29. Kim, K.K.; Prabhakar, B. Initial trust and the adoption of B2C e-commerce: The case of internet banking. *ACM Sigmis Database Database Adv. Inf. Syst.* **2004**, *35*, 50–64. [CrossRef]
30. Yousafzai, S.Y. A literature review of theoretical models of Internet banking adoption at the individual lev-el. *J. Financ. Serv. Mark.* **2012**, *17*, 215–226. [CrossRef]
31. Zhou, T. Examining mobile banking user adoption from the perspectives of trust and flow experience. *Inf. Technol. Manag.* **2011**, *13*, 27–37. [CrossRef]
32. Freier, A. Mobile Banking Customers Drive Better Retention and Higher Revenue for Institutions. 2016. Available online: www.businessofapps.com/mobile-banking-customers-drive-better-retention-andhigher-revenue-for-institutions/ (accessed on 14 August 2018).
33. Aboelmaged, M.; Gebba, T.R. Mobile Banking Adoption: An Examination of Technology Acceptance Model and Theory of Planned Behavior. *Int. J. Bus. Res. Dev.* **2013**, *2*. [CrossRef]
34. Malaquias, R.F.; Hwang, Y. An empirical study on trust in mobile banking: A developing country perspec-tive. *Comput. Hum. Behav.* **2016**, *54*, 453–461. [CrossRef]
35. Mohammadi, H. A study of mobile banking usage in Iran. *Int. J. Bank Mark.* **2015**, *33*, 733–759. [CrossRef]
36. Salimon, M.G.; Bin Yusoff, R.Z.; Mokhtar, S.S.M. The mediating role of hedonic motivation on the relationship between adoption of e-banking and its determinants. *Int. J. Bank Mark.* **2017**, *35*, 558–582. [CrossRef]
37. Singh, S. Customer perception of mobile banking: An empirical study in National Capital Region Delhi. *J. Internet Bank. Commer.* **2014**, *19*, 1–22.
38. Tam, C.; Oliveira, T. Literature review of mobile banking and individual performance. *Int. J. Bank Mark.* **2017**, *35*, 1044–1067. [CrossRef]
39. Tran, H.T.T.; Corner, J. The impact of communication channels on mobile banking adoption. *Int. J. Bank Mark.* **2016**, *34*, 78–109. [CrossRef]
40. Alalwan, A.A.; Dwivedi, Y.K.; Rana, N.P.; Williams, M.D. Consumer adoption of mobile banking in Jordan: Examining the role of usefulness, ease of use, perceived risk and self-efficacy. *J. Enterp. Inf. Manag.* **2016**, *29*, 118–139. [CrossRef]
41. Giovanis, A.; Assimakopoulos, C.; Sarmaniotis, C. Adoption of mobile self-service retail banking technologies: The role of technology, social, channel and personal factors. *Int. J. Retail Distrib. Manag.* **2019**, *47*, 894–914. [CrossRef]
42. Koksal, M.H. The intentions of Lebanese consumers to adopt mobile banking. *Int. J. Bank Mark.* **2016**, *34*, 327–346. [CrossRef]
43. Kwateng, K.O.; Atiemo, K.A.O.; Appiah, C. Acceptance and use of mobile banking: An application of UTAUT2. *J. Enterp. Inf. Manag.* **2019**, *32*, 118–151. [CrossRef]
44. Majumdar, S.; Pujari, V. Exploring usage of mobile banking apps in the UAE: A categorical regression analysis. *J. Financ. Serv. Mark.* **2021**, 1–13. [CrossRef]
45. Fenu, G.; Pau, P.L. An Analysis of Features and Tendencies in Mobile Banking Apps. *Procedia Comput. Sci.* **2015**, *56*, 26–33. [CrossRef]
46. Shankar, A.; Jebarajakirthy, C. The influence of e-banking service quality on customer loyalty: A moderated mediation approach. *Int. J. Bank Mark.* **2019**, *37*, 1119–1142. [CrossRef]
47. Siyal, A.W.; Ding, D.; Siyal, S. M-banking barriers in Pakistan: A customer perspective of adoption and conti-nuity intention. *Data Technol. Appl.* **2019**, *53*, 58–84. [CrossRef]
48. BBC. Mobile Banking Is Saving Us 'Billions' in Charges. 2017. Available online: http://www.bbc.co.uk/news/business-39290041 (accessed on 8 October 2017).
49. Ho, J.C.; Wu, C.G.; Lee, C.S.; Pham, T.T.T. Factors affecting the behavioral intention to adopt mobile bank-ing: An international comparison. *Technol. Soc.* **2020**, *63*, 101360. [CrossRef]
50. Shankar, A.; Rishi, B. Convenience matter in mobile banking adoption intention? *Australas. Mark. J.* **2020**, *28*, 273–285. [CrossRef]
51. Cheah, C.M.; Teo, A.C.; Sim, J.J.; Oon, K.H.; Tan, B.I. Factors affecting Malaysian mobile banking adoption: An empirical analysis. *Int. J. Netw. Mobile Technol.* **2011**, *2*, 149–160.
52. Jadil, Y.; Rana, N.P.; Dwivedi, Y.K. A meta-analysis of the UTAUT model in the mobile banking literature: The moderating role of sample size and culture. *J. Bus. Res.* **2021**, *132*, 354–372. [CrossRef]
53. Tan, E.; Lau, J.L. Behavioural intention to adopt mobile banking among the millennial generation. *Young Consum.* **2016**, *17*, 18–31. [CrossRef]
54. Pages. The Growth of Digital Banking Report. 2021. Available online: https://pages.caci.co.uk/rs/752-EBZ-498/images/caci-future-growth-digital-banking-report-2019.pdf (accessed on 17 September 2021).
55. Applause. 61% of People Access Mobile Banking on a Regular Basis. 2017. Available online: https://www.applause.com/blog/mobile-banking-adoption-rates/ (accessed on 2 January 2018).
56. Deloitte. The Value of Online Banking Channels in a Mobile-Centric World. 2019. Available online: https://www2.deloitte.com/us/en/insights/industry/financial-services/online-banking-usage-in-mobilecentric-world.html (accessed on 3 March 2020).

57. Farzin, M.; Sadeghi, M.; Kharkeshi, F.Y.; Ruholahpur, H.; Fattahi, M. Extending UTAUT2 in M-banking adop-tion and actual use behavior: Does WOM communication matter? *Asian J. Econ. Bank.* **2021**, *5*, 136–157. [CrossRef]
58. Geebren, A.; Jabbar, A.; Luo, M. Examining the role of consumer satisfaction within mobile eco-systems: Evi-dence from mobile banking services. *Comput. Hum. Behav.* **2021**, *114*, 106584. [CrossRef]
59. DESI. Greece in the Digital Economy and Society Index. 2021. Available online: https://digital-strategy.ec.europa.eu/en/policies/desi-greece (accessed on 2 January 2022).
60. Veríssimo, J.M.C. Enablers and restrictors of mobile banking app use: A fuzzy set qualitative comparative analy-sis (fsQCA). *J. Bus. Res.* **2016**, *69*, 5456–5460. [CrossRef]
61. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User acceptance of information technology: Toward a unified view. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
62. Hew, J.J.; Lee, V.H.; Ooi, K.B.; Wei, J. What catalyses mobile apps usage intention: An empirical analy-sis. *Ind. Manag. Data Syst.* **2015**, *115*, 1269–1291. [CrossRef]
63. Munoz-Leiva, F.; Climent-Climent, S.; Liébana-Cabanillas, F. Determinants of intention to use the mobile bank-ing apps: An extension of the classic TAM model. *Span. J. Mark.-ESIC* **2017**, *21*, 25–38.
64. Kamdjoug, J.R.K.; Wamba-Taguimdje, S.-L.; Wamba, S.F.; Kake, I.B. Determining factors and impacts of the intention to adopt mobile banking app in Cameroon: Case of SARA by afriland First Bank. *J. Retail. Consum. Serv.* **2021**, *61*, 102509. [CrossRef]
65. Venkatesh, V.; Thong, J.Y.; Xu, X. Consumer acceptance and use of information technology: Extending the uni-fied theory of acceptance and use of technology. *MIS Q.* **2012**, *36*, 157–178. [CrossRef]
66. Fishbein, M.; Ajzen, I. *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*; Addison-Wesley: Reading, MA, USA, 1975.
67. Wu, J.-H.; Wang, S.-C. What drives mobile commerce?: An empirical evaluation of the revised technology acceptance model. *Inf. Manag.* **2005**, *42*, 719–729. [CrossRef]
68. Bhatti, T. Exploring factors influencing the adoption of mobile commerce. *J. Internet Bank. Commer.* **2007**, *12*, 1–13.
69. Chung, N.; Han, H.; Joun, Y. Tourists' intention to visit a destination: The role of augmented reality (AR) ap-plication for a heritage site. *Comput. Hum. Behav.* **2015**, *50*, 588–599. [CrossRef]
70. Compeau, D.R.; Higgins, C.A.; Huff, S. Social cognitive theory and individual reactions to computing technolo-gy: A longitudinal study. *MIS Q.* **1999**, *23*, 145–158. [CrossRef]
71. Saprikis, V.; Avlogiaris, G.; Katarachia, A. Determinants of the Intention to Adopt Mobile Augmented Reality Apps in Shopping Malls among University Students. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 491–512. [CrossRef]
72. Abed, S. An empirical investigation of Instagram as an s-commerce channel. *J. Adv. Manag. Res.* **2018**, *15*, 146–160. [CrossRef]
73. Saprikis, V.; Avlogiaris, G. Modeling users' acceptance of mobile social commerce: The case of 'Instagram checkout'. *Electron. Commer. Res.* **2021**. [CrossRef]
74. Bawack, R.E.; Kamdjoug, J.R.K. Adequacy of utaut in clinician adoption of health information systems in de-veloping countries: The case of Cameroon. *Int. J. Med. Inform.* **2018**, *109*, 15–22. [CrossRef]
75. Cao, Q.; Niu, X. Integrating context-awareness and UTAUT to explain Alipay user adoption. *Int. J. Ind. Ergon.* **2018**, *69*, 9–13. [CrossRef]
76. Cimperman, M.; Brencic, M.M.; Trkman, P. Analyzing older users' home telehealth services acceptance behav-ior-applying an extended utaut model. *Int. J. Med. Inform.* **2016**, *90*, 22–31. [CrossRef] [PubMed]
77. Khalilzadeh, J.; Ozturk, A.B.; Bilgihan, A. Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry. *Comput. Hum. Behav.* **2017**, *70*, 460–474. [CrossRef]
78. Saprikis, V.; Avlogiaris, G. Factors That Determine the Adoption Intention of Direct Mobile Purchases through Social Media Apps. *Information* **2021**, *12*, 449. [CrossRef]
79. Salisbury, W.; Pearson, R.; Pearson, A.; Miller, D. Identifying barriers that keep shoppers off the world wide web: Developing a scale of perceived web security. *Ind. Manag. Data Syst.* **2001**, *101*, 165–176. [CrossRef]
80. Rahi, S.; Ghani, M.A.; Ngah, A.H. A structural equation model for evaluating user's intention to adopt internet banking and intention to recommend technology. *Accounting* **2018**, *4*, 139–152. [CrossRef]
81. Oliveira, T.; Thomas, M.; Baptista, G.; Campos, F. Mobile payment: Understanding the determinants of cus-tomer adoption and intention to recommend the technology. *Comput. Hum. Behav.* **2016**, *61*, 404–414. [CrossRef]
82. Saprikis, V. Examining behavioral intention towards social commerce: An empirical investigation in university students. In Proceedings of the 32nd IBIMA Conference, Seville, Spain, 15–16 November 2018; pp. 15–16.
83. Morgan, R.M. Relationship Marketing and Marketing Strategy: The Evolution of Relationship Marketing within the Organization. In *Handbook of Relationship Marketing*; Sheth, J., Parvatiyar, A., Eds.; Sage: Thousand Oaks, CA, USA, 2000; pp. 481–505.
84. Androulidakis, N.; Androulidakis, I. Perspectives of mobile advertising in Greek market. In Proceedings of the International Conference on Mobile Business (ICMB'05), Sydney, Australia, 11–13 July 2005; pp. 441–444.
85. Zarmpou, T.; Saprikis, V.; Markos, A.; Vlachopoulou, M. Modeling users' acceptance of mobile ser-vices. *Electron. Commer. Res.* **2012**, *12*, 225–248. [CrossRef]
86. Forsythe, S.M.; Shi, B. Consumer patronage and risk perceptions in Internet shopping. *J. Bus. Res.* **2003**, *56*, 867–875. [CrossRef]
87. Hew, J.-J.; Leong, L.-Y.; Tan, G.W.-H.; Ooi, K.-B.; Lee, V.-H. The age of mobile social commerce: An Artificial Neural Network analysis on its resistances. *Technol. Forecast. Soc. Chang.* **2017**, *144*, 311–324. [CrossRef]

88. Liébana-Cabanillas, F.; Sánchez-Fernández, J.; Muñoz-Leiva, F. The moderating effect of experience in the adoption of mobile payment tools in Virtual Social Networks: The m-Payment Acceptance Model in Virtual Social Net-works (MPAM-VSN). *Int. J. Inf. Manag.* **2014**, *34*, 151–166. [CrossRef]
89. Liébana-Cabanillas, F.; Villarejo Ramos, Á.F.; Sánchez Franco, M.J. Mobile social commerce acceptance model: Factors and influences on intention to use s-commerce. In Proceedings of the XXVI Congreso Nacional de Marketing, Elche, Alicante, Spain, 17–19 September 2014.
90. Corbitt, B.J.; Thanasankit, T.; Yi, H. Trust and e-commerce: A study of consumer perceptions. *Electron. Commer. Res. Appl.* **2003**, *2*, 203–215. [CrossRef]
91. Igbaria, M.; Iivari, J. The effects of self-efficacy on computer usage. *Omega* **1995**, *23*, 587–605. [CrossRef]
92. Lu, H.; Su, P.Y. Factors affecting purchase intention on mobile shopping web sites. *Internet Res.* **2009**, *19*, 442–458. [CrossRef]
93. Bahli, B.; Benslimane, Y. An exploration of wireless computing risks: Development of a risk taxono-my. *Inf. Manag. Comput. Secur.* **2004**, *12*, 245–254. [CrossRef]
94. Yang, K.; Forney, J.C. The moderating role of consumer technology anxiety in mobile shopping adoption: Dif-ferential effects of facilitating conditions and social influences. *J. Electron. Commer. Res.* **2013**, *14*, 334–347.
95. Leong, L.-Y.; Hew, T.-S.; Tan, G.W.-H.; Ooi, K.-B. Predicting the determinants of the NFC-enabled mobile credit card acceptance: A neural networks approach. *Expert Syst. Appl.* **2013**, *40*, 5604–5620. [CrossRef]
96. Jarvenpaa, S.L.; Tractinsky, N.; Vitale, M. Consumer trust in an Internet store. *Inf. Technol. Man-Agement* **2000**, *1*, 45–71.
97. Thatcher, J.; Perrewe, P.L. An Empirical Examination of Individual Traits as Antecedents to Computer Anxiety and Computer Self-Efficacy. *MIS Q.* **2002**, *26*, 381. [CrossRef]
98. Venkatesh, V.; Bala, H. Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decis. Sci.* **2008**, *39*, 273–315. [CrossRef]
99. Wakefield, R.L.; Whitten, D. Examining User Perceptions of Third-Party Organizations Credibility and Trust in an E-Retailer. *J. Organ. End User Comput.* **2006**, *18*, 1–19. [CrossRef]
100. Nunnally, J.C. *Psychometric Theory*, 2nd ed.; McGraw-Hill: New York, NY, USA, 1978.
101. Hair, J.; Black, W.; Babin, B.; Anderson, R. *Multivariate Data Analysis*, 3rd ed.; Pearson/Prentice Hall: Upper Saddle River, NJ, USA, 2014.
102. Bagozzi, R.P.; Yi, Y. On the evaluation of structural equation models. *J. Acad. Mark. Sci.* **1988**, *16*, 74–94. [CrossRef]
103. Fornell, C.; Larcker, D.F. Structural equation models with unobservable variables and measurement error: Al-gebra and statistics. *J. Mark. Res.* **1981**, *18*, 382–388. [CrossRef]
104. Bentler, M. Comparative it indexes in structural models. *Psychol. Bull.* **1990**, *107*, 238–246. [CrossRef] [PubMed]
105. Hu, L.-T.; Bentler, P.M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equ. Model. Multidiscip. J.* **1999**, *6*, 1–55. [CrossRef]
106. Muthén, L.K.; Muthén, B.O. Mplus for Windows 7.31. Available online: http://www.statmodel.com/verhistory.shtml (accessed on 10 December 2021).
107. Hu, P.J.; Chau, P.Y.; Sheng, O.R.L.; Tam, K.Y. Examining the Technology Acceptance Model Using Physician Acceptance of Telemedicine Technology. *J. Manag. Inf. Syst.* **1999**, *16*, 91–112. [CrossRef]
108. Singh, S.; Srivastava, R. Predicting the intention to use mobile banking in India. *Int. J. Bank Mark.* **2018**, *36*, 357–378. [CrossRef]