Determinants of using digital banking services:
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Determinants of using digital banking services:

an analysis of user satisfaction through TAM and UTAUT models with PLS-SEM

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The research we proposed has as its main objective to analyze the impact on consumer habits of the phenomenon of digital transformation in the world of banking and financial services. The future of finance has a digital DNA: old and new players have started FinTech systems, that have genetically modified the financial world. The scope of our research is to build a model that, through an extended application and reinterpretation of the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM), helps us to measure the factors affecting consumer satisfaction, retention levels towards digital banking and financial services and to investigate how these new services can impact on consumption. The importance of this research is twofold: to study the social implications deriving from the digital transformation of the financial world and to extend the models of technological acceptance through the constructs related to user satisfaction, loyalty, and propensity to consume. The study was carried out by administrating a survey to collect data, with which we extracted a sample and for testing hypotheses, we used a statistical method: a structural equation model with PLS-SEM (Partial Least Squares – Path Modeling) estimation. The proposed model showed a consistent link ($R^2 = 75\%$) with the predictors and the dependent variable "Satisfaction". The causal links between "Satisfaction" and loyalty have also been confirmed, with a 1% level of significance and with a moderate link.

keywords: UTAUT, SATISFACTION, BANKING, SURVEY, PLS.

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1 Introduction

The present work moves from observing some contemporary phenomena, in the first place the constant interest of the consumers to the best possible service and the frequent adoption of every new technological device that increases performance. No less important is the macroeconomic status of current global economies (Cellini, 2015).

Among the macroeconomic conditions, we have to mention the speculative and risky use of the so-called creative finance, that took place in the years 2007-2008. It extended the crisis of the American real estate market around the globe, involving the most important banks, financial intermediaries, managers, and small and large savers. The phenomenon has accompanied the change in the global economic paradigm and also, perhaps mainly, in the banking and financial industry. Another primary factor of importance is represented by the advanced, refined, and widespread technological innovations, which come at the forefront of everyday life so now indispensable and that have changed behavior and consumption. The digital revolution has not only changed our life and consumption habits but, obviously, also the way of doing business. Just think of the giant of digital services that is Google or the retail giant Amazon. Technological and digital innovations have been and are so invasive that they have changed almost all of how we use the services that we need. The way of doing business has become increasingly digital and faster.

In Italy digitalization started in payment services: in 1998, one-fourth of banks analyzed by Arnaudo et al. (2022) already allowed their clients to make or receive payments digitally; ten years later, in 2008, this ratio was close to 90 per cent and in 2018 all the surveyed banks provided digital access to payment services. Moreover, in the same year, 75 per cent of banks (corresponding to over 80 per cent of deposits) allowed online micro-payments and peer-to-peer money transfers through mobile devices, a share lower than 5 per cent just 4 years before. The increase in the number of banks offering payment services through mobile devices partly reflects the favour of customers for these tools to access banking services. Our focus is on the FinTech market (Villani and Giudici, 2021), in particular the change that is taking place in the world of banking services in recent years. Digital technologies invade the world of finance in an impactful and inevitable way (Villani and Giudici, 2021). The present research aims to investigate how digital banking services have entered, satisfied, and influenced people's lives. The work, in particular, aims to measure, with the aid of the PLS-SEM algorithm (Mateos-Aparicio, 2011), the degree of satisfaction (Ciavolino and Dahlgaard, 2007) and retention toward services such as online banking or mobile banking offered by consolidated (physical) banks, and by very modern ones card-account, digital services that enjoy the privileges of a prepaid card and a current account, managing it to cut the costs of opening and using a current account and they are easily managed through a mobile interface. In addition, the study investigates also the relationship between the use of these services and consumption in a broad sense.

The models underlying this research are TAM and UTAUT. The use of technology acceptance models (TAM and UTAUT) is particularly suitable for this research, they aim to measure the weight of the variables that determine the acceptance and use of this tech-

nology. Given that in our case, the technology in question represents a product/service offered to consumers, the study is aimed at measuring the factors determining satisfaction rather than acceptance.

The proposed model has as a framework the predictors of the UTAUT model to which they have added some constructs used and validated in the literature for research-related purposes. Initially, the cause-effect relationship that these constructs have on satisfaction will be studied (Cody-Allen and Kishore, 2006). Subsequently, the existence of two causal relationships will be investigated: the first between satisfaction and retention (that is the intention of wanting to continue to use the service) and the second between satisfaction and intention to consume. There is abundant literature supporting these technological acceptance models (Davis et al., 2020). The proposed model, with the relative hypotheses, consists of a reinterpretation of these.

Partial Least Squares-Structural Equation Modeling (PLS-SEM) is the statistical method used to estimate the analytical model and verify the research hypotheses. The data were preprocessed for the PLS estimation. The phase of the model assessment was carried out to have more robust coefficients and to better evaluate the hypothesis.

2 Theoretical framework and research hypothesis

2.1 The theoretical framework of TAM

The considered framework, carried out from viewpoint of sociology, lays its foundation in 1975 with the Theory of Reasoned Action (TRA) formulated by Ajzen and Fishbein (Azjen, 1980). TRA's core concept is thus that the most influential cause of a behavior is the will to pursue the behavior itself, assuming that the behavioral intention is the result of two constructs: subjective norms and attitude toward the behavior. Therefore, this is a very general model which is not related to specific behaviors. Ajzen himself expanded the TRA with a new variable, that consists of perceived behavioral control, i.e. the individual's perception of being able to or succeeding in, putting into effect the desired behavior. This is how the Theory of Planned Behavior was born (Ajzen, 1991). The Technology Acceptance Model (TAM) is the first theory that explains the reason why an individual does a specific behavior. That behavior is regarding the adoption of new technology; therefore, the method was developed by Davis in 1989, a time during which the use of personal computers on business premises started rising. The TAM's goal was to obtain a good prediction about the adoption of new technology in a work contest. It does that through two key constructs: Perceived Usefulness (capabilities of an instrument to be used advantageously) and Perceived Ease of Use (Davis et al., 2020). Both TAM and TPB are derived from TRA. TAM is the first theory that, unlike TRA and TPB which are models aimed at identifying the causes of general behavior, focuses on identifying the factors that determine the technological adoption (specific behavior). The TAM will be a precursor of the literal strand of models of technological acceptance. The innovation's growth kept growing and with it was born 1995 the Innovation Diffusion Theory by Rogers (2010), a theory that explains how society adopts a technological innovation and how that technology is diffused over time. Starting from his first elaboration,

TAM has been the subject of many reviews and empirical testing. Venkatesh and Davis proposed the TAM2 approach in 2000; the core assumption is that the perceived utility and use behavior is influenced by other variables not present in the previous theory: the "social influence process" (beliefs, individual opinions, subjective norms, voluntariness, and image) and the "cognitive instrumental processes", that includes facilitating conditions and self-efficacy (relevance to work, quality of output, demonstrability of results, perceived ease of use) (Venkatesh and Davis, 2000).

In 2003 Davis, Venkatesh, and other authors, to achieve a unified model that would integrate the main studies on the theme of technology adoption, developed the model named Unified Theory of Acceptance and Use of Technology (UTAUT), a framework which is shown very promising for manage the analysis of process related to technological change in regarding work and organization. UTAUT's objective is to explain its main variables: the "behavioral intention" and "user behavior"; it does that by studying the relationship between its four independent variables and the "Behavioral Intention", which in turn impacts "Use behavior" (Venkatesh et al., 2003). Later the UTAUT model was modified by Venkatesh, Thong & Xu in 2012, It has added three constructs: "hedonic motivation" (defined as the degree to which technology is perceived as pleasant), "price value" (trade-off between perceived benefits and monetary costs), and "habit" (defined as the time spent using technology), which aim to integrate the model into a consumer context and to go beyond its limits (Venkatesh et al., 2012).

2.2 Literature review and hypotheses

Following the UTAUT approach, the proposed theoretical model uses the four main effects or exogenous constructs by Davis et al. (2020). They are good for explaining concepts such as performance found in mobile banking use, efficiency related to making a mild effort, user-friendliness, and the level up to which we consider irrelevant the common opinion about using these services: "The degree to which a person believes that using a particular system would enhance his or her job performance"; "The degree to which a person believes that using a particular system would be free from effort" (Davis, 1989).

The four main effects by Davis et al., 2020 are:

Performance Expectancy (PE). It is defined as the degree of conviction of a person regarding the fact that the use of a particular system increases the level of their working performance (Davis, 1989) (Davis et al., 2020).

This construct explains how individuals believe that the use of technology can help them with the achievement of the predetermined working goal. This variable includes some concepts derived from early theories like "Perceived usefulness" (TAM model); extrinsic motivation (Motivation Model) and outcome expectations (Theory of Planned Behavior; Ajzen (1991)). According to the authors, it is the variable that is most able to explain the model. In this study, PE indicates the perceived benefit of the customer from the use of mobile banking, accelerating routine banking transactions like payments and credit transfers. Therefore, PE indicates the impact of the assured financial convenience of mobile banking. The perceived convenience is put about the remote availability 24/7 of

financial services through mobile banking.

Effort Expectancy (EE) is defined as the degree of conviction of a person regarding the fact that the use of a particular system is effortless (Davis, 1989). EE is about the expectation of an individual to pursue a light effort associated with the use of technology. This variable derives from three constructs: perceived ease of use, perceived complexity, and (actual) ease of use. The experience turned out to be particularly relevant in the case of the valuation of brand-new technology. The Performance Expectancy and Effort Expectancy constructs are direct descendants of TAM's Usefulness and Ease of use. In this study, EE is about the expectation of an individual to pursue a light effort associated with the use of digital banking services. Precisely, assuming the existence of a positive utility conferred by the light effort which is necessary to use a mobile application. It is reasonable to assume that the utility conferred by the service can be the main reason that customers adopt these systems to make banking operations.

Social Influence (SI) is defined as the degree to which a person perceives that other relevant people consider that he must use the new technology (Venkatesh et al., 2003). SI measures the degree to which the individuals perceive relevant other opinions circa the importance of technology use. The variable has the purpose of evaluating if the individual behavior might be influenced by the opinion of others in case of the use (or not) of technology. This variable has a significantly inferior weight when analyzing contexts in which the adoption of technology is compulsory (like in the workplace) turning into a variable more appropriate in contexts of voluntary adoption (Venkatesh et al., 2012). In this case, SI measures the degree to which the individuals perceive relevant other opinions and our hypothesis about the importance of mobile banking services use. The reflection consists in assuming that relatives, friends, and influential people could recommend banking services with good feedback. Especially in the last period, characterized by the expansion of the FinTech field, we were able to observe the increasing use of these services by our acquaintances which encourage us to become a user.

Facilitating Conditions (FC) express the degree to which an individual believes that exists a technical infrastructure to support the use of the system (Venkatesh et al., 2003). The construct is defined as the degree to which the individuals consider the existence of useful support for technology use. This definition captures different concepts already present in other constructs particularly frequent in literature, i.e. the perceived control (Theory of Planned Behavior) and the ease of use. Each of these is operationalized to include relevant aspects of the technology itself or the environment where it is used. With FC construct we want to investigate how easy it is for individuals to use the applications regarding mobile banking services. Technologies become smarter and for this reason, we expect that also self-conscious people find it easy and enjoyable the use of PC and smartphones.

The fifth and last exogenous construct is about both mere security and perceived privacy related to sensitive data strictly bound to a current account (Merhi et al., 2019). The first endogenous construct concerns the satisfaction degree of consumers who are customers of banking digital services. The study of satisfaction has been considered appropriate since technology is freely adopted by consumers (Liberati and Mariani (2018); Cody-Allen and Kishore (2006)). The retention results as another key construct for the

study to understand whether individuals would continue using services, they are already customers of. The explorative branch of the research concerns the possible causal link between satisfaction and intention to consume, to find out whether mobile banking smart services facilitate and affect the propensity to consume.

Here, we introduce two constructs:

the first is about the perceived privacy that is related to the individual right to control personal data gathering and use in digital form or not. Also, privacy is defined as the right to prevent a voluntary disclosure of personal information. Anyway, privacy is drastically increased following the ease with which it is possible to collect and elaborate large and detailed personal data. This concern is due to sensitivity, to data's value, and the potential perceived risk caused when individuals compile online-form with their personal information.

The second is about perceived security. It is defined as the degree to which individuals believe it is safe to transmit their personal information via online channels. The fear of security breaches is one of the main obstacles that individuals encounter when they need to relay sensitive information online. This has been the subject of many studies, which list security as one of the most critical barriers to the acceptance and growth of e-banking (Merhi et al., 2019).

We merged the two constructs Perceived Privacy and Perceived Security into a single construct. The reason for this choice lies in the fact that for privacy we mean the right to secretly on personal and sensitive data, data that may be those of a credit card. If they were stolen, we would have both damages to sensitive information and a real monetary theft. Therefore, this construct has the scope to measure how much the customers perceive as a sure service of mobile banking both pure safety and privacy. We named this construct **Perceived Privacy (PP)**.

The next construct that we explain is **Satisfaction (SAT)**. SAT is the response variable for all the constructs explained so far. In its formulation the UTAUT model uses as response variables the "behavioral intention" and the "use behavior", it was a model that in literature has found great application in the acceptance of technologies in the workplace (Cody-Allen and Kishore, 2006); (Indriati and Agustina, 2018); (Wan et al., 2020). The research that used this model was often aimed at understanding how the subjects of a given organization welcomed the use of IT in the performance of their tasks, when the technologies considered were not voluntary but necessary for the work done. The units taken into consideration for this job are consumers who have voluntarily chosen to be customers of banking services. Therefore, rather than measuring the user's behavioral intention and use behavior towards the technological service, we set as our first objective to study the degree of satisfaction resulting from the use of mobile banking.

Now we consider the last two constructs: "Intention to consume" (IC) and "Retention" (RET). Retention is the action aimed at preserving something, in this case, preserving a behavior, linked to the intention to continue to use a technological service. This construct has been hypothesized based on the variables "behavioral intention" and "use behavior", aimed at identifying the loyalty of consumers. Given that the survey was addressed to a sample of users of this technological service, the idea was to investigate

the degree of customer loyalty.

The construct "Intention to consume" (IC) has a fundamental role in the research, whose last aim is to investigate a possible relationship between the satisfaction resulting from the use of mobile banking services and the propensity to consume online, which we could define as smart consumption. Unlike the SAT and RET constructs, the IC construct has no evidence in the literature: the models of acceptance of technology do not assume a relationship between the use of technology and consumption. However, we do not think that the assumption we have made is too strong. From our personal experience with banking services, and from the experience of relatives and people close to us, we noticed a great correlation between mobile banking and online purchases, digital consumption has soared also due to the circumstances dictated by the health emergency. Speed is becoming a fundamental component of globalization, speed is represented by the business model in which Amazon is the leader that, for each user, aims to make a purchase come true in less than a minute. The vessel to keep up with this type of speed in purchases is precisely the use of mobile banking apps, which allows you to leave the physicality of payments behind, transforming -day by day- the wallets as we know them into digital wallets. For these reasons, we want to hypothesize a causal link between satisfaction with mobile banking services and the propensity to consume (Cellini, 2015).

The theoretical framework is graphically represented in Figure 1, together with the causal links assumed.

Hypothesis 1): Performance Expectancy (PE) influences positively customer satisfaction related to mobile banking services adoption in the Italian context.

Hypothesis 2): Effort expectancy (EE) influences positively customer satisfaction related to mobile banking services adoption in the Italian context.

Hypothesis 3): Social influence (SI) affects positively customer satisfaction related to mobile banking services adoption in the Italian context.

Hypothesis 4): Facilitating conditions (FC) affects positively customer satisfaction related to mobile banking services adoption in the Italian context.

Hypothesis 5): Perceived Privacy (PP) influences positively customer satisfaction related to mobile banking services adoption in the Italian context.

Hypothesis 6): The degree of satisfaction will have a strong positive impact on retention, related to the intention to maintain the use of digital banking services.

Hypothesis 7): The degree of satisfaction related to banking services will have a positive impact on the intention towards consumption through online purchases.
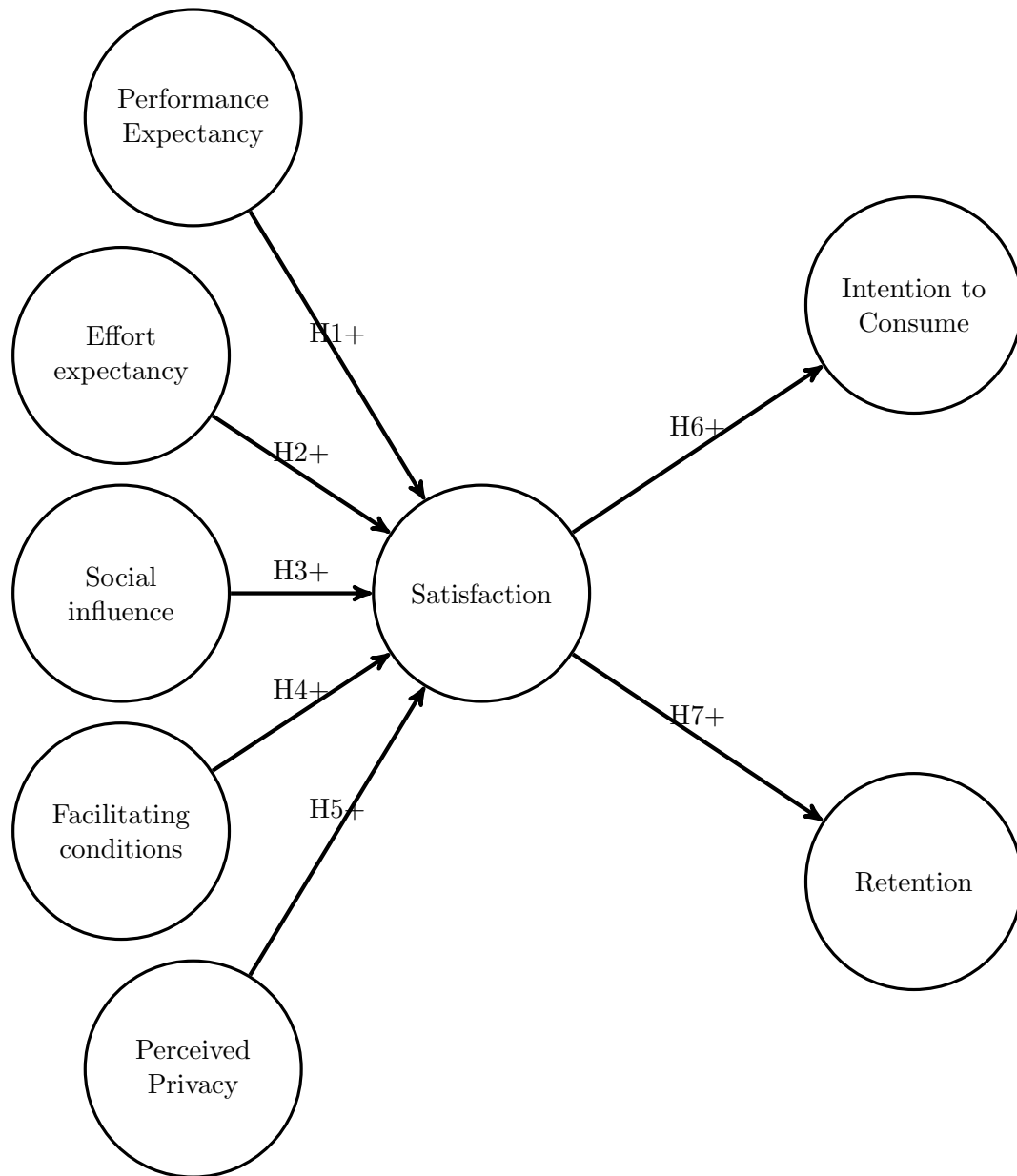
Figure 1: Theoretical framework represented in path model

3 Methodology

3.1 Questionnaire structure

To test the above-mentioned hypotheses, we undertake a study based on the respondents to whom the questionnaire is submitted. The target respondents were customers of a digital banking service (Boari and Nai Ruscone, 2015).

Please note that the semantic choice and the content of the items listed here were not designed by the writer but have roots in the questionnaires validated (Merhi et al., 2019); (Wan et al., 2020), which use items similar to measure constructs of technology acceptance models (Table 1) (Davis et al., 2020). Moreover, following the classical TAM and UTAUT approaches, we adopted a five-point Likert scale to measure the intensity of responses.

The questionnaire was tested by a pilot survey on a small test of respondents. In this way, we collected feedback to improve the question wording, modify or remove not useful questions and improve the overall questionnaire quality and time to finish. In Table 1, we report the final set of items for each construct.

3.2 Data collection and description

A computer-assisted Web interview survey (LimeSurvey open-source platform) was conducted to reach as many respondents as possible and obtain as much information as possible in a short time. The respondent was informed about the anonymous form of the questionnaire and about the time time to complete the survey (approximately five minutes). We collected a total of 289 responses with a non-response rate equal to 36%. The theoretical population to which we have referred consists of all Italian users of digital banking services. Since the questionnaire was conducted via the CAWI system, the population reached consisted of all users of these services using online platforms. The sample was then extracted by randomly administering the questionnaire on telematic channels (social networks and e-mail).

We asked respondents the socio-demographic questions reported in Table 2. 53% of the sample is composed of 18-25 years old people that are students, there are also adults and quite different age ranges. The sample is quite balanced in terms of gender (56% male and 44% female). 66% of respondents have a degree, 14% have a post-graduate formation, 17% have a high school diploma and only 2% of the sample have a secondary school diploma.

After for screen out the sample compared to the topic of the research, we have inserted in the survey three questions reported in Table 3: "How long have you had an online bank account?"; "Do you generally use online subscriptions?"; "How high-tech do you think you are?". We asked the respondents these questions to study the degree of loyalty to digital banking services and digital services in general. Since the research first involves the study of satisfaction, we needed a sample of people who are inclined to use such systems. From these data (Table 3), we can easily see that people define themselves as technological, and they usually use online services.

Performance Expectancy [PE]	PE1	The application is useful for doing my task
	PE2	Using the app allows me to do my task quickly
	PE3	Using the app allows me to increase my performance
	PE4	Using the app allows me to increase my productivity
Effort Expectancy [EE]	EE1	My interaction with the app is clear and understandable
	EE2	It's easy for me to become good at using the app
	EE3	I find the application easy to use
	EE4	I find it easy to make the app do what I want
Social Influence [SI]	SI1	People I think are influential advise me to use the application
	SI2	People, I frequently think I should use the app
	SI3	People that are important to me have good regard for me if I use the app
Facilitating Conditions [FC]	FC1	I have the resources to use the app
	FC2	I have the skills to use the application
	FC3	The app is not compatible with other apps that I use
Perceived Privacy [PP]	PP1	The use of the app allows me to have enough privacy
	PP2	I'm comfortable with the amount of privacy I have when I use the app
	PP3	My data is protected when I use the banking app
	PP4	The app adopts the necessary mechanisms for the security of the
	PP5	I think the app has enough technical qualities to provide that the system is not breached
Satisfaction [SAT]	SAT1	Overall the service offered through the app has good quality
	SAT2	The banks that use this system are good suppliers
	SAT3	I'm generally satisfied with the service
	SAT4	I'm generally satisfied because this service operates on the internet
	SAT5	I'm generally satisfied with my bank that offers me this service
Retention [RET]	RET1	I intend to continue to use a service like this rather than not continue to use it
	RET2	I intend to continue to use the service shown rather than any other services
	RET3	If I could I would like to continue to use the service in the future
	RET4	I would advise my colleagues to use these baking services
Intention to Consume [IC]	IC1	I'm more likely to shop online (i.e Amazon) because the app makes it easier for me
	IC2	Since I have an online current account I benefit from shopping from home
	IC3	I find it easier to transfer money from one current account to another through the app
	IC4	I find it easier to use the bank transfer tool through the app

Table 1: The relevant indicators used in the model

The scaling method used for measuring the constructs consists of the Likert scale (Boari and Nai Ruscone, 2015). We chose five scale labels (from "strongly agree" to "strongly disagree"), to express the degree of agreement or disagreement with the proposed statement as an Item. The data collected through the Likert scale offers an excellent compromise between practicality and functionality in statistical methods.

Variables	Responses	Frequencies	%
Age	18-25	152	53
	26-35	78	27
	36-45	7	2
	46-55	21	7
	more than 55	31	11
Sex	Male	162	56
	Female	127	44
Education	Postgraduate	42	14
	Graduate	191	66
	High school	48	17
	Secondary school	6	2
	Other	2	1
Occupation	Student	153	53
	Worker	96	33
	Pensioner	15	5
	Entrepreneur	11	4
	Unemployed	6	2
	Other	2	3

Table 2: Sample characteristics

4 Statistical Analysis

4.1 Structural equation modeling with PLS-PM

We used structural equation modeling (SEM) to test the hypotheses. SEM is a family of multivariate statistical methods designed to test a conceptual or theoretical model and this family is widely used in the behavioral sciences (Mateos-Aparicio, 2011). Common SEM Methods include confirmatory analysis, path analysis, and latent growth modeling. This statistical method commonly involves the use of two models: a measurement

Questions	Responses	Frequencies	%
How long have you had an online bank account?	More than a year	221	83
	Almost a year	29	11
	A few months	13	6
	Just opened	2	1
Do you generally use online subscriptions?	Yes, usually I do	149	57
	Yes, It happened	80	30
	No, I do not	36	12
How high-tech do you think you are?	A Great Deal	80	30
	Much	121	46
	Somewhat	47	17
	Little	16	6
	Never	1	1

Table 3: Technological self-evaluation

model (or outer model) that defines the constructs (Ciavolino, 2012) using one or a set of items (or observed variables), and a structural model (or inner model) that explains the links between these latent variables using a system of simultaneous regression equations. There is a further distinction in SEM's family: covariance-based techniques, whose fame is known for LISREL, and variance-based techniques, among them partial least squares path modeling (PLS-PM or PLS-SEM) is the leading representative (Ciavolino et al., 2022).

Many are the topic in which PLS-SEM is used for research, such as accounting Nitzl (2016), strategic management (Hair et al., 2012), management performance (Ciavolino and Dahlgaard, 2009), e-business (Anderson and Swaminathan, 2011), human behavior (Nasution et al., 2020), marketing Al-Msallam and Alhaddad (2016) and job satisfaction (Ciavolino and Dahlgaard, 2009).

This methodology has found a large application for studying human behaviors. The technology acceptance models are ideal for studying adoption behavior, if we speak of voluntary adoption, we often find the application of PLS for market and marketing research.

The advantage of using PLS-SEM over covariance-based is based on PLS's characteristic: its flexibility related to the cause-effect relationship models that allow estimating both formative models and reflective because the method includes two types of outer models: formative and reflective (Pelagatti et al., 2012).

PLS can be used for estimating path models when sample sizes are small and for estimating a very complex model (i.e. with many latent and manifest variables).

In literature, there is wide use of reflective models to measure latent variables, in which co-variation among the measures is caused by variation in the underlying latent factor. Through the PLS-SEM we have a unique estimation approach: the algorithm finds the

best solution for measuring blocks between measures and constructs that maximize predictive power between the constructs themselves.

Reflective indicators of a latent variable should be internally consistent. In the formative model changes in the measures are hypothesized to cause changes in the measurements of the constructs, in contrast with it in the reflective model the items associated with a latent variable are interchangeable. Usually, a single construct is measured with a multi-item scale with bullet points such as good-bad.

4.2 Partial Least Squares estimation and assessment

We have performed the analysis in the R environment 4.1 (R Core Team, 2020) using the library named "seminr" (Ravand and Baghaei, 2016). We chose a structural model with a path-weighting (Mode A) scheme, (correlation between a latent variable and the items associated with it) which is the most suitable scheme for reflective links. The results of the model assessment are shown in Table 5, Table 6, Table 7, and Table 8 and the estimated path model is in Figure 2.

The graphic conventions used by the package "seminr" for the path model in Figure 2 are: hexagons for the latent variables and rectangles represent manifest variables. Arrows linking squares to hexagons indicate the relationship between a latent variable and its manifest variable. Arrows linking hexagons to hexagons indicate the causal relationship between latent constructs.

For assessing the SEM-PLS, we followed the classical two-step approach: the assessment of the outer model; and then the assessment of the inner model.

4.3 Outer model assessment

To evaluate a reflective link, we need to study validity and reliability. Usually, the first criterion considered is internal consistency reliability. Cronbach's α is the traditional index for internal consistency, which provides an estimate of reliability based on the inter-correlations of observed manifest variables. This index gives a measure of the one-dimensional nature of a latent variable but generally underestimates the reliability of internal consistency when the number of indicators is less than seven. For this reason, it is more appropriate to use the other two measures of composite reliability: Dijkstra-Henseler's Rho (ρ_a) and Dillon-Goldstein's Rho (ρ_c) (Henseler et al., 2015); (Dijkstra and Henseler, 2015).

An internal consistency reliability value greater than 0.7 in the early stage of research and a value greater than 0.8 in the advanced stage are considered good. The composite reliability and Cronbach's values (Table 4) confirm good internal consistency for all constructs.

To assess convergent validity, we use two criteria: Average Variance Extracted (AVE) and outer loadings (or loadings). Convergent validity is a concept that wants to investigate what the indicators related to a construct have in common. Therefore, the elements that are indicators (measures) of a construct must share (or converge) a high percentage

of variance.

Generally, indicators with loadings' values between 0,40 and 0,70 should only be eliminated when the elimination of each indicator corresponds to a general increase in reliability. Below the value of 0.40, an indicator must be eliminated. A loadings value greater than 0.7 is good (Leguina, 2015).

The loadings below 0.4 are SI3, FC4, IC3, and IC4, they should be deleted. The loadings between 0.4 and 0.7 are SI4, TR4, OS5, RE1, and IC5, removing SI4, TR4 and IC5 reliability values have been improved. A value of the AVE index equal to or greater than 0,50 indicates that the construct explains more than half of the variance of its indicators. The AVE's values are good and also all the values of the Reliability are good, except for the Social Influence variable, which has a lower value of ρ_a, AVE and α. Probably the scale relates to SI is not unidimensional.

We confirm the presence of convergent validity and internal consistency for all the constructs except for Social Influence.

Follow, this to assess the measurement model and the discriminant validity.

It measures how much a construct differs from other constructs: each latent variable must explain a single concept and it must not happen that two variables latent explain the same concept. The presence of discriminant validity implies the uniqueness of a construct in terms of the information explained. There are some measures to study the discriminant validity: the heterotrait-monotrait (HTMT) ratio (Table 5), the Fornell-Larcker (FL) criterion (Table 6), and the cross-loadings (Table 7). The FL criterion measures that a construct must explain more variance in its indicators than in the other latent variables. In statistical terms, the AVE of a construct should be greater than the latent variable's highest squared correlation with any other latent variable (Leguina, 2015).

HTMT is the ratio of between-trait correlations and within-trait correlations. At the numerator we have the Heterotrait correlation: the average correlation between the manifest variables of a construct compared to another. At the denominator we have the correlation Monotrait: it is the correlation among all measurement variables of a single construct. An HTMT ratio close to 1 between two constructs indicate a lack of discriminating validity. We expect the relationship to be less than 0.9 so that the internal correlation is greater than the external one. So if this index is less than 0.9 there is a discriminating validity (Leguina, 2015). The two criteria are satisfied, and we conclude the outer model assessment confirms the presence of discriminant validity.

Please look at Tables 5, 6, and 7 to see the results of the outer model assessment.

4.4 Inner model assessment and results

The first criterion for this assessment is the coefficient of determination R^2 of the endogenous variables. As multiple regression, we use the adjusted R^2 as the criterion to prevent distortions caused by the number of predictors. It is difficult to provide accurate general rules for acceptable R^2 values because they depend both on the complexity of

α	ρ_c	ρ_a	AVE
Performance Expectancy	0.882	0.919	0.888
Effort Expectancy	0.852	0.900	0.860
Social Influence	0.520	0.758	0.572
Facilitating Conditions	0.834	0.900	0.895
Perceived Privacy	0.911	0.934	0.912
Satisfaction	0.840	0.887	0.850
Retention	0.824	0.883	0.849
Intention to Consume	0.846	0.897	0.848

Table 4: Average Variance Extracted (AVE)

PE	EE	SI	FC	PP	SAT	RE	IC
Performance Expectancy	.	.	.	-	.	.	.
Effort Expectancy	0.347	.	.	.	.	.	.
Social Influence	0.511	0.489	-	.	.	.	.
Facilitating Conditions	0.117	0.303	0.184	-	.	.	.
Perceived Privacy	0.336	0.646	0.565	0.379	.	.	.
Satisfaction	0.667	0.797	0.683	0.232	0.826	.	.
Retention	0.597	0.613	0.528	0.354	0.693	0.825	.
Intention to Consume	0.422	0.581	0.448	0.334	0.704	0.706	0.567

Table 5: heterotrait-monotrait (HTMT) ratio

PE	EE	SI	FC	PP	SAT	RE	IC
Performance Expectancy	0.861	.	.	.	.	.	.
Effort Expectancy	0.302	0.832	.	.	.	.	.
Social Influence	0.342	0.344	0.722	.	.	.	.
Facilitating Conditions	0.088	0.251	0.127	0.866	.	.	.
Perceived Privacy	0.308	0.574	0.387	0.338	0.860	.	.
Satisfaction	0.560	0.691	0.461	0.207	0.743	0.782	.
Retention	0.498	0.530	0.345	0.289	0.613	0.693	0.810
Intention to Consume	0.370	0.495	0.289	0.287	0.618	0.608	0.474

Table 6: Fornell-Larcker (FL) criterion

the model and the discipline of research. Chin et al. (1998) describe R^2 value values of 0.67, 0.33, and 0.19 in PLS-SEM respectively substantial, moderate, and weak. If

	PE	EE	SI	FC	PP	OS	RE	IC
PE1	0.887	0.246	0.291	0.110	0.288	0.518	0.472	0.323
PE2	0.797	0.306	0.248	0.103	0.234	0.454	0.319	0.257
PE3	0.918	0.242	0.319	0.121	0.343	0.506	0.459	0.387
PE4	0.835	0.253	0.320	-0.042	0.183	0.446	0.458	0.300
EE1	0.366	0.840	0.301	0.170	0.377	0.588	0.468	0.319
EE2	0.199	0.763	0.160	0.226	0.376	0.494	0.424	0.332
EE3	0.139	0.853	0.292	0.303	0.586	0.568	0.394	0.559
EE4	0.289	0.870	0.369	0.151	0.556	0.639	0.475	0.433
SI1	0.449	0.258	0.808	0.027	0.304	0.387	0.275	0.227
SI2	0.199	0.342	0.811	0.185	0.292	0.351	0.184	0.185
SI4	0.011	0.114	0.502	0.065	0.241	0.243	0.317	0.228
FC1	0.124	0.230	0.148	0.910	0.345	0.222	0.284	0.276
FC2	0.053	0.207	0.106	0.927	0.300	0.159	0.247	0.269
FC3	0.029	0.216	0.056	0.752	0.211	0.138	0.207	0.190
PP1	0.154	0.490	0.285	0.320	0.896	0.589	0.462	0.560
PP2	0.248	0.521	0.369	0.217	0.913	0.637	0.566	0.644
PP3	0.417	0.425	0.361	0.183	0.857	0.669	0.560	0.451
PP4	0.151	0.615	0.377	0.365	0.857	0.654	0.473	0.581
PP5	0.337	0.410	0.264	0.372	0.771	0.636	0.565	0.423
0S1	0.300	0.656	0.393	0.270	0.750	0.767	0.494	0.647
0S2	0.423	0.531	0.340	0.096	0.632	0.805	0.652	0.380
0S3	0.469	0.626	0.424	0.081	0.626	0.870	0.580	0.470
0S4	0.489	0.501	0.361	0.299	0.523	0.778	0.482	0.535
OS5	0.565	0.334	0.262	0.037	0.299	0.679	0.504	0.302
RE1	0.487	0.240	0.072	0.366	0.375	0.425	0.677	0.352
RE2	0.465	0.371	0.267	0.095	0.441	0.542	0.818	0.400
RE3	0.261	0.496	0.312	0.226	0.491	0.577	0.862	0.319
RE4	0.437	0.553	0.401	0.276	0.640	0.669	0.870	0.461
IC1	0.238	0.440	0.260	0.149	0.525	0.518	0.356	0.869
IC2	0.122	0.431	0.204	0.225	0.503	0.469	0.312	0.825
IC6	0.429	0.371	0.226	0.242	0.494	0.478	0.500	0.809
IC7	0.422	0.394	0.262	0.330	0.522	0.539	0.402	0.804

Table 7: Cross-loadings

the structure of the model explains an endogenous variable by a few (i.e. one or two) exogenous variables, a moderate R^2 might be acceptable. The results of R squared are reported in Table 8.

Researchers can also assess how the removal of a certain predictor construct affects an endogenous construct's R^2 value, this metric is the effect size (f^2). Table 9 indicated that the f^2 was insignificant for Social Influence and Facilitating Conditions, medium for Performance Expectancy and Effort Expectancy, and large for Perceived Privacy and Satisfaction for responsiveness as suggested by Cohen (2013).

The statistic Q-square establishes if the model has predictive relevance or not. Table 10 suggested that the model in this study has good predictive relevance. Q^2 values should be larger than zero for a specific endogenous construct to indicate the predictive accuracy of the structural model for that construct. Q^2 values higher than 0; 0.25 and 0.50 depict small, medium, and large predictive relevance of the PLS-SEM (Hair et al., 2019).

The individual path coefficients (Table 8) of the PLS structural model can be interpreted as linear bivariate correlation coefficients, which are equivalent to the standardized beta coefficients of ordinary least squares regression. The path coefficients, whose signs have been predetermined with the hypotheses, are used to confirm the casual- inks assumed. between latent variables. Paths that possess an algebraic sign contrary to expectations do not support the formulated hypotheses (Aria et al., 2018).

To study the magnitude and significance of path coefficients we used bootstrap, a non-parametric resampling method. The bootstrapped standard error is used to calculate empirical t values and confidence intervals (Leguina, 2015). The bootstrap analysis is shown in Table 11.

Independent variable	Dependent variable	R square	Strength
Performance Expectancy Effort Expectancy Social Influence Facilitating Conditions Perceived Pivacy	Satisfaction	0.756	Substantial
Satisfaction	Retention	0.481	Moderate
Satisfaction	Intention to Consume	0.369	Moderate

Table 8: Inner model assessment: coefficient of determination

Consistent with the theoretical model defined in Figure 1, our analyses confirm the satisfaction with mobile banking services. The exogenous variables that determine and significantly impact satisfaction represent efficiency, performance (PE), speed, practicality, reduction of excessive effort (EE), security, and perceived privacy (PP). We also confirm the presence of a causal link between Satisfaction to Retention and Satisfaction to Intention to consume.

Structural Paths	F square	Effect Size
PE $\Rightarrow$ SAT	0.273	Medium
EE $\Rightarrow$ SAT	0.287	Medium
SI $\Rightarrow$ SAT	0.019	.
FC $\Rightarrow$ SAT	0.015	.
PP $\Rightarrow$ SAT	0.498	Large
SAT $\Rightarrow$ RET	0.925	Large
SAT $\Rightarrow$ IC	0.585	Large

Table 9: f² (F square)

Dependent variable	Q square	Predictive Power
Satisfaction	0.4567	Large
Retention	0.2955	Medium
Intention to Consume	0.2501	Medium

Table 10: Q² (Q square)

Structural Paths	Original Est.	Boot. Mean	T Stat.	P-value	2.5% CI	97.5% CI
PE $\Rightarrow$ SAT	0.3	0.3	9.448	< 0.001***	0.235	0.361
EE $\Rightarrow$ SAT	0.33	0.326	6.769	< 0.001***	0.227	0.416
SI $\Rightarrow$ SAT	0.077	0.080	1.836	0.074	-0.003	0.161
FC $\Rightarrow$ SAT	-0.066	-0.06	-1.709	0.093	-0.129	0.019
PP $\Rightarrow$ SAT	0.454	0.454	10.528	< 0.001***	0.373	0.541
SAT $\Rightarrow$ RET	0.693	0.694	16.932	< 0.001***	0.612	0.771
SAT $\Rightarrow$ IC	0.3	0.3	9.448	< 0.001***	0.516	0.699

Table 11: Inner model assessment: Bootstrapped structural paths, *** $p \leq 0.01$

Specifically, the path coefficient of PE on SAT is significant at 1%, with a coefficient equal to 0.3. Therefore, the expectation related to the performance has a strong positive impact on customer satisfaction with mobile banking services. We confirm the H1. The path coefficient of EE on SAT is significant with a coefficient equal to 0.326 (p-value < 0.001). Therefore, the expectation related to a reduction of effort resulting from the adoption of these systems has a strong positive effect on satisfaction. We confirm the H2. The path coefficient of SI on SAT is not significant (p-value = 0.074), the coefficient of 0.077 is very low and the bootstrap confidence interval includes zero. We reject the hypothesis (H3) of a positive influence of the social influence on satisfaction, this effect is weak. We must consider that SI could be not crucial for customer satisfaction. The

path coefficient of FC on SAT is not significant (p-value = 0.093). This result rejects hypothesis H4. Effect sizes (f^2) also confirm that FC and SI do not participate in determining the SAT (dependent variable). The path coefficient of PP on SAT is significant (p-value < 0.001), with a coefficient of 0.454. We confirm the hypothesis (H5) of a strong positive impact of Perceived privacy on satisfaction. The path coefficient of SAT on RET is significant (p-value < 0.001), with a coefficient equal to 0.693. The value of this path coefficient is very high; therefore we confirm a strong impact of Satisfaction on Retention.

The hypothesis (H6) is confirmed. In the end, the path coefficient of SAT on the IC is significant (p-value < 0.001), also this coefficient is high (0.516). We confirm the hypothesis (H7) of a strong positive satisfaction with the propensity to consume.

5 Discussion

5.1 Limitations and Recommendations for Future Study

Regarding the possible limits of the study, we have to consider that the theoretical population of reference for the study is made up of all Italian customers of digital banking services. Given that the questionnaire has been administered via the web, the accessible population is formed by users on online platforms. It is a potential limit for this work that the extracted sample may not be representative of the theoretical population for the prevalence of young people. In addition, the questionnaire started with a filter question asking for access requirements to be customers of a digital banking service (Mobile/Online banking). The use of web channels together with filter demand has probably attracted most young people to the questionnaire, who are certainly more accessible through these channels. For future research, we recommend extracting a sample that is balanced in terms of age classes, as close as possible to the reference population.

5.2 The implication of the study

The contribution to the study is twofold: the first is methodological, which consists in revisiting the models of technological acceptance (TAM and UTAUT) towards a framework related to the voluntary use of the technology in question and the correlation with consumption; the second is an application, which consists in the use of the proposed model to estimate, in the Italian context, satisfaction from the use of digital banking services and exploratory research into the correlation between satisfaction and consumer intent. To understand whether such systems encourage and facilitate the consumption of goods and services through digital channels.

In the UTAUT model, the SI construct measures the degree of social influence that interferes with the use of the technology under consideration; in our model, SI is exogenous to the endogenous SAT construct; therefore, it investigates the relationship between the
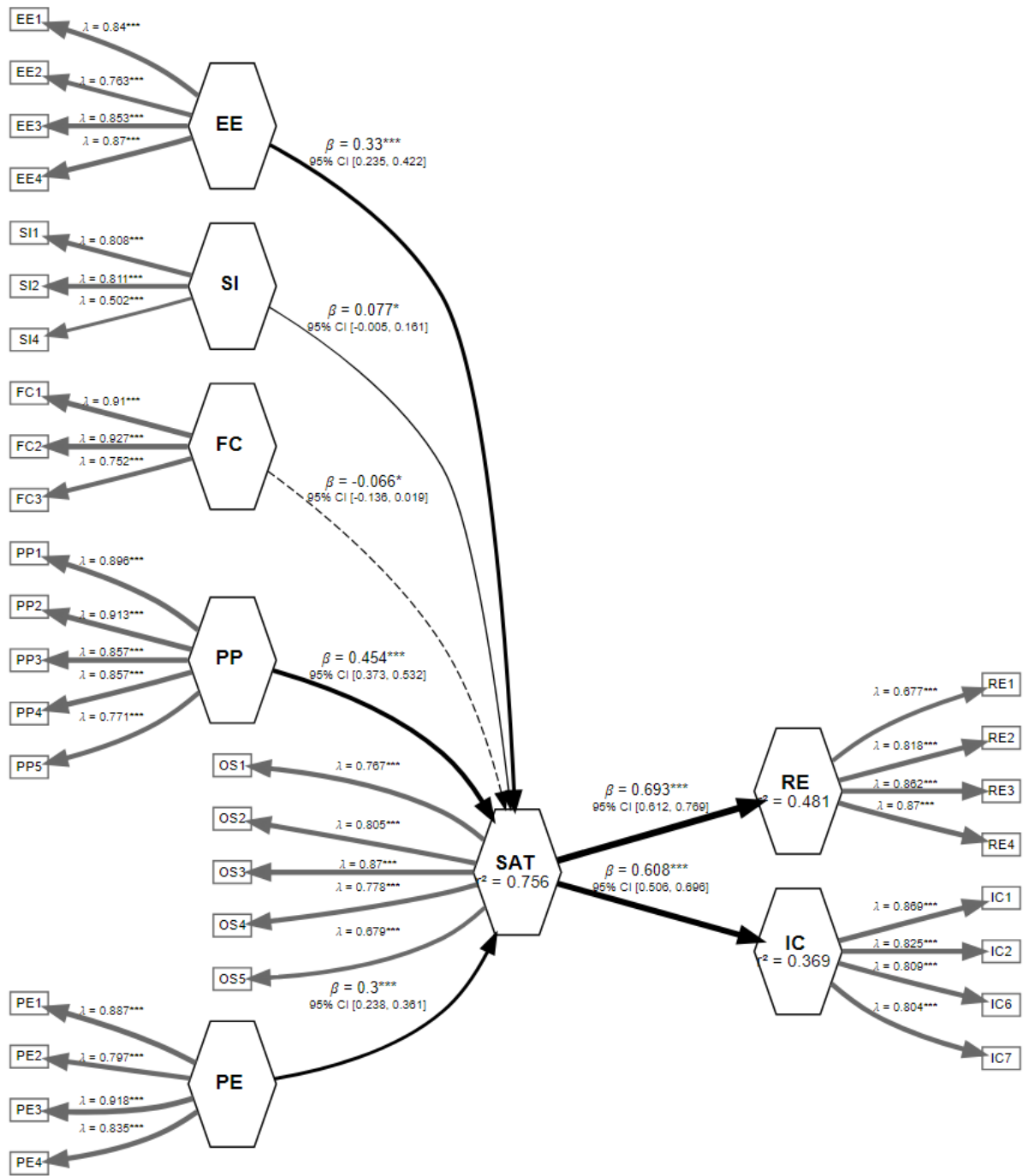
Figure 2: Bootstrapped model

social influence and the satisfaction, a relationship that has not been impactful. The first appropriate reflection is that the SI construct could be more suitable to evaluate the relationship with technology when it is not still growing in the market and the demand is not yet loyal to this technology. The survey was addressed to an audience of users who already had relations with the banking service in question; the variables used to describe the quality of the sample showed that most respondents were already inclined to use mobile banking. 57% of the sample said that they usually use digital subscriptions; cumulatively 76% of respondents placed themselves between the categories "Very" and "Very much" and self-defined as technological people and about 83% of respondents were already loyal to mobile banking for more than a year. We are therefore dealing with an audience of consumers who are already used to living in a "smart" world, full of technological shortcuts that facilitate operations. It should also be recognized that society, and in particular the large industry of services and financial and media services in general have now influenced bank customers to move from "old" doors (ATM) to the latest and smart applications.

Moving the attention to the relationship between Facilitating Conditions and Satisfaction, we asked in our survey for an evaluation of the ease of use (Davis, 1989) of the digital app interface and service offer. From a social point of view, we can reflect on the age classes of users of smart devices: non-native digital people are less likely to intuitively use apps and digital services; on the contrary, young people are daily in contact with apps. The programmers, when deciding the interface of the app, must take into account the customers who will use it; therefore, they will choose a guided path if the app will be used by a "senior" user. This path is, however, in contrast with a young clientele, which is accustomed to quick interfaces that need one or two clicks to get to the desired result. For this reason, a young person might find the app's interface clunky and judge it negatively or find it difficult to evaluate. On the other hand, even a non-confident person with This kind of technology might not be able to express a sincere judgment. These could lead us to a bias problem in the answers, caused by possible random opinions. We're talking about a possible non-sample error due to the human component. Because the value of the FC coefficient on SAT is not significant, we do not consider this hypothesis confirmed for the research.

The exogenous variables that determine and significantly impact satisfaction represent efficiency, performance (PE), speed, practicality, reduction of excessive effort (EE), security, and perceived privacy (PP), managing to explain 75% of the variability (R-squared). In its turn, satisfaction (SAT) can explain 50% of the variability linked to loyalty (RET) and 38% of the variability linked to a propensity to consume (IC).

Technological acceptance models (TAM and UTAUT) are a good starting framework for analyzing new and relevant social phenomena, naturally with a technological background. The model proposed is suitable for analyzing voluntary technological acceptance and extending this acceptance to a consumer environment.

5.3 Conclusion

Often in the past to use certain services, there was the need to go personally to the office or the authorized places; now we can use them comfortably from our smart devices. If we consider leisure time as a positive component of consumer usefulness, the perception of usefulness resulting from the time saved due to these smart devices are significantly very high.

To consider also the reduction of the costs from the consumers, as an example, through very modern "card-account", through these privileges, they succeed to cut the costs of the opening and use of a traditional bank account. And this cost reduction is especially from suppliers with the reduction of the so-called physical costs legacies to the business premises.

Moreover, think about the tons of paper consumed or the used ink cartridges categorized as special waste. They are objects that are used in offices daily, which contribute socially to the distribution of costs related to the negative externalities associated with them. The point of traceability is crucial for the security and legality of transactions with related problems of tax evasion. These are real examples that contribute to determining the satisfaction and loyalty of consumers toward these digital services.

Mobile banking, chosen as a heuristic field of application for the survey conducted, contributes to the completion of the Fintech digital economic transition process through the loyalty of consumers to the widespread and daily use of every banking, financial, and insurance transaction. For the entire sector, it will be essential to extract knowledge about the factors that encourage the use of smart modes for a potentially unlimited audience. A real network of money transfers on digital platforms has been established and the propensity to reduce the use of cash in favour of the immateriality of money has grown. The first cards with conversion services of a Cryptocurrency with legal tender are also being created. We are, in the end, immersed in a globalized network in which capital and goods are exchanged from one point of the world to another in very limited times. The trend is transversal and concerns households with low income for ordinary consumption, as well as large capital, moved for speculative purposes or productive investments.

The future doesn't come back.

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