VIII Encontro Brasileiro de Administração Pública
ISSN: 2594-5688
Sociedade Brasileira de Administração Pública

ARTIGO

BEHAVIORAL PROFILE AND ASPECTS INFLUENCING RESISTANCE TO FINANCIAL INCLUSION AND SAVINGS FOR LOW-INCOME POPULATION

ETTORE DE CARVALHO ORIOL, ERIKA LISBOA, LAURO EMILIO GONZALEZ FARIAS

GT 17 - PRÁTICAS E ESTRATÉGIAS DE GESTÃO AMBIENTAL, SOCIAL E DE GOVERNANÇA NO ÂM

VIII Encontro Brasileiro de Administração Pública, Brasília/DF, 3 a 5 de novembro de 2021.
Sociedade Brasileira de Administração Pública (SBAP)
Instituto Brasileiro de Ensino, Desenvolvimento e Pesquisa (IDP)
Brasil

Disponível em: https://sbap.org.br/

Behavioral Profile and Aspects Influencing Resistance to Financial Inclusion and Savings for Low-Income Population

ABSTRACT

Using the 3M behavioral theory developed by Mowen (2000), we try to answer the question, "what is the influence of behavioral profile on the various elements that improve financial citizenship?" The method used was the CFA, and the SEM-CB applied to the data of a survey developed during the research of the PLAN CDE in 2017. The results indicate that all the constructs of financial inclusion studies were influenced by the behavioral profile in low-income population. The contribution was to demonstrate that behavioral characteristics, skills, influence financial inclusion, helping in to build inclusion policies for these citizens.

Keywords: Financial Inclusion; Low-income population; 3M theory.

INTRODUCTION

In recent years, the economic stagnation experienced by Brazil has contributed to the stability of social inclusion of the less favored classes and even growth in poverty (Sotomayor, 2021). However, economic growth alone is not enough for this inclusion to happen (Chibango, 2014). The exclusion caused by poverty can be reduced through public policies to include these citizens (Sela et al., 2020; Lal, 2018).

The Banco Central do Brasil (tradução: Central Bank of Brazil) - BCB develops actions that could be considered focused on the financial inclusion of the low-income population since the 1970s. The BCB started the program by encouraging microcredit, moving on to microfinance, financial inclusion, and arriving at what we now call financial citizenship. The financial citizenship agenda started in 2015 and provided citizens with education, protection, and financial inclusion (Sela et al., 2020).

The relevance of this topic is due to the social and economic importance that the inclusion of low-income people can bring to them, their families, and the country. Long-term economic gains, such as an increase in macroeconomic development (Jeanneney & Kpodar, 2011), and the inclusion of low-income people in the economy provide better living conditions and even health, showing that this issue is essential for all countries, especially developing countries like Brazil (Allen et al., 2016; Sela et al., 2020).

Poverty can be defined as the lack of resources to purchase goods and services, from basic items such as food, water, shelter, health to other aspects such as services in general (Bhagwati & Panagariya, 2013; Arvind, 2008). According to article 6 of the 1988 Federal Constitution of Brazil - CF88, "education, health, food, work, housing, transportation, leisure, security, social security, protection of motherhood and childhood, and assistance to the destitute are social rights" (Constituição da República Federativa do Brasil de 1988, 1998). Thus, the government's social inclusion policies and provision of these services should be guaranteed regardless of economic conditions (Allen et al., 2016).

Poverty can also be seen as a form of social exclusion (Davis, 2002). The social exclusion makes it impossible for these people to access basic services that could improve their participation in society, including access to banking services (Allen et al., 2016). Access to the formal institutions of society can improve the protection of citizens' rights as advocated by the CF88 (Banerjee & Somanathan, 2007). Therefore, banking can play a role in inclusion and development (Allen et al., 2016; Jeanneney & Kpodar, 2011).

There seems to be a gap in identifying the skills that can improve the financial inclusion of low-income social classes (Friedland et al., 2012; Lloyd & Friedland, 2016). Thus, we identified the research question, "what is the influence of behavioral profile on the various elements that improve financial citizenship?" To answer this question, we used behavioral theory through the 3M Model (Mowen, 2000; Asebedo et al., 2018), which seeks to identify the influence of individuals' various psychological characteristics on their actions and reactions to consumption.

The justification for our study lies in the premise that improving the knowledge about issues that influence the low-income population may help both financial institutions and policymakers to develop strategies and tools that improve financial inclusion and development. Financial inclusion improves the living conditions of these people (Allen et al., 2016) and can increase economic development (Lal, 2018). In addition, most of the identified studies are supply-oriented and focused business models and arrangements instead of personal skills and profiles of the users of financial services (Friedland et al., 2012; Lloyd & Friedland, 2016).

The method used for this investigation was quantitative research through a survey.

(Bryman, 2012). Data analysis was performed using Structural Equation Modeling - SEMCB (Hair et al., 2010; Malhotra et al., 2017). The results achieved indicates that the behavioral profile influences the risk propensity (greater or lesser interest in taking risks or accepting new ways of dealing with the situations faced) and that this propensity to take risks influences the resistance to the use of technology to access banking services, the use of the bank account, access to banking services, savings and loans.

The theoretical contribution of this research was to adapt the 3M Model (Mowen, 2000) to the reality of low-income social class banking in a developing country (Carrieri & Correia, 2020). A more robust theoretical view about the elements that interact in the relationship of low-income people with banking services and savings can greatly improve these people's lives, contributing to their personal growth, family, and the country. In practice, this information can be used by bank managers and public administrators to improve the banking of low-income social classes, bringing with it all the gains from this inclusion.

LITERATURE REVIEW

Behavioral Profile and the Banking Process of Low-income Social Classes

We use the behavioral theory (Asebedo et al., 2018: Chetty, 2015) to analyze low-income citizens' behavioral profiles in the way they are associated with banking. The behavioral theory seeks to analyze how people behave in the face of challenges, using their personalities and other intrinsic characteristics for this analysis (Hamilton & Morgan, 2018). Within this theory, we will use an adaptation of the Motivation and Personality -3M Model that seeks to organize the various characteristics hierarchically to provide a model for analyzing the influence of these characteristics on behavior (Mowen, 2000).

The 3M Model identifies various behaviors within the consumer chain, from financial behaviors to online shopping to gambling behaviors (Davis and Runyan 2016; Kang & Johnson 2015; Jadlow and Mowen 2010). To explain this relationship of the behavioral profile to the other aspects studied, 3M treats personality with five major elemental characteristics: openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism (Costa & McCrae 1992).

These five major groups of most elementary traits give rise to four others that emerge on the surface, becoming visible and influencing the behavior of consumers in general. These traits are formed directly and indirectly by these elementary characteristics. The originated or surface traits are described by Mowen (2000) as elemental, compound, situational, and surface. The surface trait gives rise to the saving behavior, for example, and is the most enduring within the 3M design (Asebedo et al., 2018). The surface is defined as the "enduring tendency of consumers to behave concerning a product category or behavioral domain" (Mowen 2000, 23).

We used the 3M Model as a basis for the behavioral profile analysis adapting the types described by Mowen (2000) to the Brazilian reality and limiting ourselves to only these two stages, elemental and surface, of the analysis, not dealing with compound traits and situational traits (Mowen, 2000, 21). This form of adaptation is treated in the literature as a great contribution to the development of science. It seeks to observe how theories developed in central countries within the administration are adapted and used in different realities from those that gave rise to the theory (Carrieri & Correia, 2020).

The adaptation occurred on two levels, first in the ways of observing the five major elementary characteristics. In this case, they were adapted to only three characteristics and their possible interactions, forming a total of 10 possibilities, described as conservative, planned and disorganized, and mixed cases. This way of organizing the personalities is more focused on the cognitive elements causally linked to financial issues, extending to other life issues more tangentially. From these three elementary characteristics, the disposition to take more or less risk in the personal relationship with finances, in general, arises directly and indirectly. The influence exerted by these characteristics is catalyzed by what Mowen (2000) called surface, already defined earlier. Thus, in our study, the surface is represented by the individual's relationship to their greater or lesser exposure to risk, exemplified as resistance to adopting new technologies (Kim et al., 2018; Venkatesh et al., 2003; Venkatesh et al., 2016), or as greater or lesser willingness to use the services offered by banks (Davis & Runyan 2016; Jadlow & Mowen 2010).

Decision-making is directly linked to restricting the amount of information an individual can rationalize (Schilbach et al., 2016). Within this premise, their behavioral profile arising from elementary characteristics and exteriorized by surface in their more conservative or more risk-prone disposition will greatly influence decision-making (Asebedo et al., 2018; Hamilton & Morgan, 2018). When that consumer belongs to the low-income social class, this lack of information and difficulty in rationalizing decisions is even more apparent (Bertrand et al., 2006; Gerhard et al., 2018). This happens because there is an educational gap and a much deeper information asymmetry than in other social classes

(Hamilton & Morgan, 2018). Other elements studied, such as resistance to technology for the use of banking services, or resistance to adopting the services offered, or even the amount of knowledge about finance, are also influenced by the behavioral profile of greater or lesser aversion to risk-taking, demonstrated by the surface originated from the elementary characteristics of individuals.

Hypothesis Construction

Using technology to access the bank is important for the inclusion of the unbanked belonging to low-income social classes and can lead to great social inclusion and economic growth for countries (Albuquerque et al., 2014; Kim et al., 2018; Pazarbasioglu et al., 2020). Digital inclusion via broadband internet for these citizens has become an inclusion tool that has changed the way people accessed their bank accounts (Albuquerque et al., 2014).

For the literature addressing internet access by low-income citizens, this growth happens due to several factors, including technical factors as behavioral factors (skills) (Alkhowaiter, 2020; Kim et al., 2018; Patil et al., 2017). Focusing on behavioral factors, our study seeks to identify the influence of attitudes and behaviors on technology adoption for accessing banking services, with such studies considered second-order (Van Dijk & Van Deursen, 2014). This focus on skills seeks to observe various aspects of adopting technology as a tool for accessing banking services (Ferrari, 2012; Van Dijk & Van Deursen, 2014). This adoption is shaped by behavioral profile and perceived benefits in this direct and indirect relationship (Ligon et al., 2019).

Resistance to technology adoption is another important factor in the behavioral profile towards using technology to access banking services (Kim et al., 2018). This resistance may prevent low-income class citizens from accessing banking services to help them in their daily lives (Patil et al., 2017). Even if access to banking services is a must for these citizens, resistance to technology can become a barrier and make this access very difficult (Venkatesh et al., 2003; Venkatesh et al., 2016).

Hypothesis 1 *- Behavioral profile positively influences the adoption of technological media use in financial matters.*

The influence exerted by the behavioral profile on banking happens because the perception of gain with this banking, especially in the low-income social class, is not always perceived, even though it is proven that this banking improves the economic performance of the country (Jeanneney & Kpodar, 2011; Lal, 2018). Resistance to banking is another factor that has a strong impact on the availability of banking services in the low-income social class (Napoli & Obar, 2014). In addition to not having access to these services, there is a perception that one needs to have plenty of financial resources to access banking services (Hamilton & Morgan, 2018). Services such as microcredit and others aimed exclusively at the low-income social class often do not reach the target citizens because of these people's resistance to banking (Lal, 2017).

Works aimed at solving this impasse are developed by several financial institutions, both in Brazil and in several countries worldwide (Jeanneney & Kpodar, 2011). However, there is still a large portion of the unbanked world (Allen et al., 2016). Thus, in addition to providing the technical means for this access, it is necessary to check the influence of behavioral profiles on banking (Asebedo et al., 2018). The influence makes banking more precarious, even when it happens because the citizen tends not to take advantage of all available services, resisting the adoption of only the essential and often mandatory services by situations external to this banking such as payment and salaries or other benefits offered by government public policies.

Hypothesis *2 - Behavioral profile positively influences the adoption of banking.*

Another point discussed in the literature is the influence of the perceived costs of using the banking services offered to low-income citizens (Carvalho et al., 2016). This is an essential point for banking, and the behavioral profile of citizens can facilitate or hinder the perception of gains and costs involved in the adoption of these services (Fernbach et al., 2015; Shah et al., 2012). Thus, for greater adoption of services, perception of gains greater than the costs involved is necessary (Gonzalez, 2020). This perceived gain will generate adherence to each behavioral profile and lead to greater adherence to these services (Mullainathan & Shafir, 2013).

Hypothesis 3 *- Behavioral profile positively influences the adoption of means of using banking services.*

The choice to save for later consumption or to consume immediately is related to the behavioral profile of the citizen (Asebedo, 2018; Mowen et al., 2009). Technology adoption and banking act as facilitators of saving behavior (Gerhard et al., 2018). However, the behavioral profile has the greatest weight in this decision (Bertrand et al., 2006). Social class has a strong influence on saver behavior (Gerhard et al., 2018). Thus, the behavioral profile acts differently on citizens depending on their social class. The decision to save in the low-income social class is strongly influenced by the behavioral profile and the moment's circumstances (Bertrand et al., 2006). Considering that low-income people have little slack in their budgets to save, a profile focused on this attitude can generate consistent behaviors with long-lasting results (Mosca & McCrory, 2016). Having high control over impulses and generating continuity in their attitudes can greatly help this process (Bernheim et al., 2015; Haushofer & Fehr, 2014).

Hypothesis 4 - *Behavioral profile positively influences the saver profile.*

Adopting and pursuing financial knowledge can greatly improve how citizens handle their resources (Hamilton & Morgan, 2018). Citizens who do not know about finances tend to be sloppier as their financial commitments (Lloyd & Friedland, 2016). Behavioral research has observed that knowledge tends to improve citizens' attitudes towards day-to-day challenges, especially concerning managing their assets and resources (Chetty, 2015; Schilbach et al., 2016; Wakita et al., 2000). The more knowledge about finances a person has, the better their behavior will be about managing their resources (Gerhard et al., 2018; Hamilton & Morgan, 2018). Understanding whether the behavioral profile can significantly influence the adoption of knowledge about finance can help improve actions aimed at this adoption, especially among the low-income social class.

Hypothesis 5 - *Behavioral profile positively influences the adoption of knowledge about finance.*

Another important point in studying behavioral profiles with banking is the influence of this behavioral profile on borrowing. Several reasons lead a citizen to borrow (Hamilton & Morgan, 2018); however, the resistance to borrowing is linked much more to the behavioral profile related to the spending profile than to investments to produce new earnings (Hamilton et al., 2018). This happens because a good part of the loans are linked to personal or household budget imbalance, which causes restriction of the possibility of consumption (Botti et al., 2008; Cannon et al., 2018; Chen & Miller, 2012; Kraus et al., 2009; Shah et al., 2012) and not to productive investments (Bernheim et al., 2015; Bertrand et al., 2006; Botti et al., 2008; Dupas & Robinson, 2009). Understanding the influence of a citizen's behavioral profile on their intention to borrow can clarify their behavior in several other aspects within the banking process, especially among low-income classes (Hamilton et al., 2019).

Hypothesis 6 - *Behavioral profile influences the intention to borrow.*

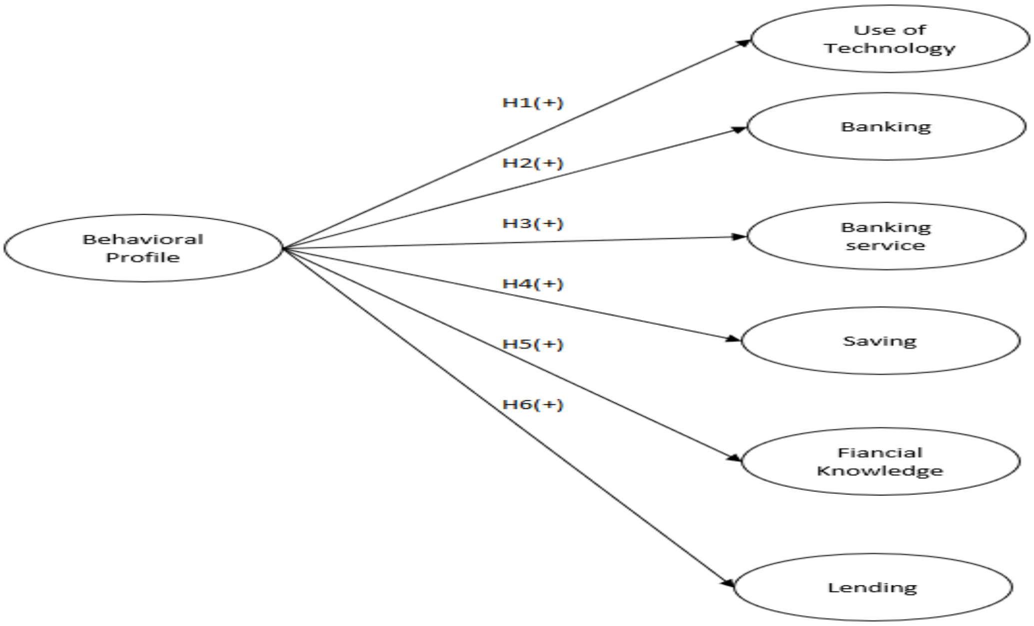

Figure 1: Model tested in this research

METHOD

The research conducted in this paper is organized as objectivist and functionalist (Cunliffe, 2010). It is based on a literature review for the theoretical construction of a hypothetical model to be falsified (Popper, 2008). This model seeks to answer how and why the behavioral profile influences various aspects related to the bankability of low-income classes (Whetten, 1989).

The research approach was quantitative, with primary data extracted from a survey conducted for Plano CDE in partnership with the Getulio Vargas Foundation - FGV and the research group GVcemif - Center for Microfinance Studies and Financial Inclusion. The research aimed to identify the attitudinal profiles of the low-income CDE classes concerning banking in its various aspects. Data collected by this research were collected during this survey, and the sample was carried out in a probabilistic way, enabling the statistical generalization of the results and findings.

The data collection instrument was a survey applied by the "CDE Plan" that generated a report used to account for the results. This data was reworked by building reflective indicators that sought to capture respondents' perceptions about the constructs researched (Bryman, 2012; Hair et al., 2010; Malhotra et al., 2017). We used data treatment as most of the questions were descriptive, and when grouped, they came to reflect the respondents' higher or lower perception of each construct studied (Bryman, 2012; Pedhazur & Schmelkin, 1991).

The survey participants were composed of a sample of 1505 respondents belonging to social classes CDE - (low-income). These classes are formed by people with monthly family per capita income below US$ 229,60 in November 2017. The survey was conducted during 2017 and applied electronically and by telephone to randomly selected respondents.

We analyzed the collected data using Structural Equation Modeling with Covariance Matrix Based - SEM-CB (Hair et al., 2010; Malhotra et al., 2017) results presented and discussed. This type of analysis tests the validity of a theory by testing for convergent validity, discriminant validity, construct validity, and structural model validity (Bryman, 2012; Hair et al., 2010; Malhotra et al., 2017; Pedhazur & Schmelkin, 1991).

We performed the tests starting with the CFA - Confirmatory Factory Analyze, which checks the validity of the measurement instrument, measurement model. CFA seeks to demonstrate the efficiency and effectiveness of reflective indicators in measuring the constructs used in the structural model (Hair et al., 2010; Malhotra et al., 2017).

The SEM-CB validation and analysis of the structural model checks all the validities of the model, both measurement and structural, because it works in only one stage (Hair et al., 2011; Hair et al., 2014). This methodology is the best for theory testing because it integrates all elements, unlike other methods that perform the analyses in two stages, measuring the model first and only then developing the structural model, such as the Structural Equation Modeling - Partial Least Square - SEM-PLS method (Hair et al., 2011; Jöreskog and Wold, 1982; Reinartz et al., 2009).

Other authors consider the SEM-CB and SEM-PLS model complementary, with SEM-CB being for theory testing and SEM-PLS for data analysis of already tested theories or analysis of theories with formative indicators (Diamantopoulos et al., 2007; Gudergan et al., 2007). According to Hair et al. (2011; p. 144), the specific use for each method is

> "[i]f the goal is predicting key target constructs or identifying key 'driver' constructs, select PLS-SEM. If the goal is theory testing, theory confirmation, or

> comparison of alternative theories, select CB-SEM. If the research is exploratory or an extension of an existing structural theory, select PLS-SEM."

The program used for the calculations was the "RStudio" version "1.3.1093" through the "Lavaan" package. This package works with the SEM-CB and the Robust Maximum likelihood estimator - MLM, indicated for samples larger than 250 respondents, even with data without multivariate normal distribution (Mardia, 1980). The MLM method can calculate reliable indicators for large samples, even when the indicators are not multivariate (Hair et al., 2010; Malhotra, 2017). In our research, the number of respondents is well above the minimum required and amounts to 1505 respondents.

Common Method Bias

To prevent the data analyses from being impacted by Common Method Bias, we applied some remedies indicated by related literature (Fuller et al., 2015; Podsakoff et al., 2003, 2012). The procedural remedies applied were: the use of a probabilistic sample by drawing from the target population of the survey, with personal unfamiliarity between the respondent and the interviewer to avoid social desirability; the development of the questionnaire considered psychological separation, decreasing the possibility of related response between questions, seeking to design the questions to avoid that the respondent manages to generate a response bias purposely to fit what he thinks is what the interviewer wants to hear; the care with the ambiguity of the questions, which sought to be very objective, descriptive, avoiding the confusion of understanding among respondents. The questions were not written with parallel measurements (Likert scale of 5 or 7 points, for example), nor with repetition of measurements between them, avoiding confusion between the items being asked.

We also used the Exploratory Factory Analysis of Harman - EFA test (1976) indicated by Podsakoff et al. (2003) and tested by Fuller et al. (2015) to verify the possibility of bias. Our tests indicate that this possibility is almost null since the comparison between the model with only one factor and the proposed model showed very discrepant values (Fuller et al., 2015).

Table 1: Common Method Test - Harman's test.

Harman's test

Model test x EFA test only factory			
	Model Value	EFA Value	Literature Limit
χ^2	577.64	2373.20	
df	133	152	
p-value	0.000	0.000	< 0.05
χ^2/df	4.34	15.61	< 5.0
GFI	0.947	0.755	> 0.90
CFI	0.923	0.505	> 0.90
TLI	0.901	0.443	> 0.90
RMSEA	0.056	0.13	> 0.08

RESULTS

The sample was 1,505 respondents randomly selected throughout Brazil, with respondents from large, medium, and small cities. The gender distribution was 49.96% females and 50.04% males. The sample was 51% with income between US$ 114.34 and US$ 251.31 per capita, considered average, 42% with income between R$ 102.00 and US$ 114.34 per capita, considered Poor, and 7 % with an income of up to US$ 31.18 per capita, considered Extremely Poor. The age groups studied were 18 to 29 years old with 27%, 30 to 49 years old with 43%, and 50 to 69 years old with 31%. Finally, the sample distribution across the country's regions was 9% in the North, 35% in the Northeast, 7% in the Midwest, 39% in the Southeast, and 11% in the South.

The measurement scale test indicated a good fit with Cronbach's Alpha 0.783 higher than the value indicated by the academic literature, that is, higher than 0.70 (Hair et al., 2010).

Confirmatory Factor Analysis - CFA test

We started the test of the proposed model by observing the measurement model and the validity of its questionnaire items. The test of this proposed model was conducted through Confirmatory Factor Analysis - CFA, which seeks to verify that the measurement model formed by the chosen indicators reflects the variances of the latent variables to be measured. Our tests for convergent validity and Global Fit of the measurement model showed that the criteria previously established by the academic literature were met, as shown in Table 2 (Hair et al., 2010; Tabachnick & Fidell, 2013).

Table 2: Observed Variables

Latent Variables

		Estimate	Std.Err	z-value	p-value	Std Estimate
Tecno_Use =~	P17	1.599	0.057	28.159	0.000	0.945
Tecno_Use =~	P18	0.459	0.016	27.936	0.000	0.832
Tecno_Use =~	P20_1	0.259	0.015	16.999	0.000	0.555
BanKing =~	P22_1	0.536	0.035	15.419	0.000	0.598
BanKing =~	P23	0.963	0.050	19.156	0.000	0.884
BanKing =~	P24_1	0.719	0.034	21.340	0.000	0.747
BanKing =~	P24_2	0.110	0.020	5.413	0.000	0.394
BanKing =~	P24_3	0.088	0.019	4.567	0.000	0.400
BanKing =~	P24_10	0.353	0.034	10.446	0.000	0.469
Service =~	P28	1.009	0.045	22.333	0.000	0.839
Service =~	P29_11	0.260	0.018	14.707	0.000	0.387
Service =~	P29_21	0.261	0.015	17.594	0.000	0.442
Saving =~	P31	0.824	0.014	58.516	0.000	1.185
Saving =~	P32	0.176	0.014	12.491	0.000	0.425
Lending =~	P51_1	1.000			0.000	0.997
Lending =~	P53	0.331	0.017	18.972	0.000	0.558
Finac_Knowledge =~	P58	1.000			0.000	1.000
Behavioral =~	P42_1	1.000			0.000	0.575
Behavioral =~	P47	0.761	0.037	20.494	0.000	0.632

Note: Global fitted value: $\chi^2 = 571.04$; df = 133; $\chi^2/df = 4.29$; GFI = 0.949; CFI = 0.923; TLI = 0.901; RMSEA = 0.056

We tested the correlation between the constructs, indicating no risk of multicollinearity between the constructs (Ringle et al., 2014; Hair et al., 2010). We tested discriminant validity by the method of Fornell and Larcker (1981), as indicated by comparing the square root of the AVE shown on the diagonal of Table 3 and the other correlations between the latent variables of the model indicating the existence of discriminate validity.

Table 3: Construct Correlation Matrix

Correlation

	Tecno_Use	BanKing	Service	Saving	Lending	Finac_Know	Behavioral
Tecno_Use	**0.915**						
BanKing	0.464	**0.721**					
Service	0.578	0.593	**0.717**				
Saving	0.242	0.195	0.240	**1.041**			
Lending	0.101	0.063	0.145	0.025	**0.904**		
Finac_Knowledge	0.256	0.204	0.273	0.088	-0.024	**1.000**	
Behavioral	0.624	0.511	0.488	0.370	0.108	0.362	**0.594**
Composite Reliability	0.890	0.788	0.682	1.058	0.877	-	0.518
AVE	0.837	0.519	0.514	1.084	0.817	-	0.353

Note: Values in the central diagonal represent the square root of the extracted average variance - AVE and indicate the discriminat validity according to criteria of Fornell and Larcker

Structural Model Analysis

We tested the structural model using SEM-CB and identified that all hypotheses were significant at 5%, considering that all hypotheses formulated were supported by the empirical data (Hair et al., 2010; Malhotra et al., 2017). The weight of influence of the Behavioral profile on the other constructs ranges β from 0.624 to 0.108, indicating that some constructs have strong to low influence (Hair et al., 2010). The amount explained by the Behavioral profile of the variation of the constructs studied ranges from R^2 of 0.390 to 0.012.

The model fit indices presented exceptionally good values, well above the minimum indicated by the literature, bringing validity to the model tested and significance to the conclusions demonstrated here (Bagozzi & Yi, 1988; Bentler, 1990; Bentler & Bonett,1980; Hair et al., 2010; Malhotra et al., 2017; Nunnally & Bernstein, 1994; Tabachnick & Fidell, 2013).

Table 4: Regression test - Hypotheses Test

Regressions

		Estimate	Std.Err	z-value	p-value	Std.all	R^2	Hypotheses
H1(+) Tecno_Use	~ Behavioral	0.799	0.061	13.110	0.000	0.624	0.390	Supported
H2(+) BanKing	~ Behavioral	0.595	0.051	11.625	0.000	0.511	0.261	Supported
H3(+) Service	~ Behavioral	0.560	0.050	11.211	0.000	0.488	0.239	Supported
H4(+) Saving	~ Behavioral	0.398	0.037	10.784	0.000	0.370	0.137	Supported
H5(+) Finac_Knowledge	~ Behavioral	0.388	0.028	13.980	0.000	0.362	0.131	Supported
H6(+) Lending	~ Behavioral	0.109	0.028	3.866	0.000	0.108	0.012	Supported

Note: Global fitted value: χ^2 = 577.64; df = 133; χ^2/df = 4.34; GFI = 0.947; CFI = 0.923; TLI = 0.901; RMSEA = 0.056

DISCUSSION OF RESULTS

The results presented in the analysis of the collected data indicate that all constructs analyzed were significant at 5%. This means that the results of the regression weight β and the power of explanation R^2 can be analyzed to identify which elements related to the banking of the low-income social class are more influenced by their behavioral profile (Bagozzi & Yi, 1988; Nunnally & Bernstein, 1994; Tabachnick & Fidell, 2013).

Based on these results, we can analyze each of the hypotheses. We start by observing the hypothesis that receives greater influence from the behavioral profile, the technology use, H1 with β = 0.624 and R^2 of 0.390. This result indicates that the behavioral profile greatly influences how low-income people deal with technology to access their bank accounts and other banking services (Albuquerque et al., 2014; Kim et al., 2018; Pazarbasioglu et al., 2020). This finding is in line with the theory that indicates this to be an especially important point for banking and decreasing resistance to new technologies and their use in accessing banking services (Ferrari, 2012; Van Dijk & Van Deursen, 2014). Another important point is that the more familiar with the technology, the lower the resistance to its use, especially when the perception of benefits is easily identified (Patil et al., 2017). In this case, the behavioral profile geared towards greater risk-taking acts as a strong facilitator of adopting new technological means to access banking services (Ligon et al., 2019).

The influence of behavioral profile on banking, H2 with β = 0.511 and R^2 = 0.261, also reached a value considered expressive (Hair et al., 2010). These values indicate that the behavioral profile influences the choice of low-income citizens to have or not to have a bank account. People with a bolder behavioral profile have more bank accounts than those considered more conservative (Allen et al., 2016). This finding aligns with the theory that indicates that this access is a growth factor for the person, the family, and the country, including these people, which brings long-term macroeconomic gains for the country (Jeanneney & Kpodar, 2011; Lal, 2018). With this result, investing in public policies that decrease the resistance of more conservative people to become bankable will bring gains for the whole society (Allen et al., 2016).

In addition to whether a citizen has a bank account, banking services need to reach that citizen and be designed for their needs (Sela et al., 2020; Allen et al., 2016). Thus, the behavioral profile influences banking services, H3 with β = 0.488 and R^2 = 0.239. This influence indicates that low-income class citizens need to identify gains in using banking services to seek these services (Fernbach et al., 2015; Shah et al., 2012). The more conservative the low-income citizen, the greater their resistance will be, and the greater should be the perception of gain for their adherence to these services (Mullainathan & Shafir, 2013).

The influence of the behavioral profile on saving, H4, with β = 0.370 and R^2 = 0.137, was still considered large for influence analysis in social sciences (Hair et al., 2010). In the case of saving, besides the behavioral profile having the highest weight, several other factors, such as the moment's circumstances, influence (Bertrand et al., 2006). Let's consider the indirect influence of resistance to technology adoption (Vankatesh et al., 2016) and Banking and adoption of banking services (Gerhard et al., 2018). We can understand how the Behavioral profile influences the intention to save among low-income citizens. The more open to taking risks, the more likely they are to use banking means to save, with a more constant profile and more lasting results (Mosca & McCrory, 2016). However, having high control over impulses and generating continuity in their attitudes can greatly help this process (Bernheim et al., 2015; Haushofer & Fehr, 2014).

The hypothesis that behavioral profile influences financial knowledge, H5, with β = 0.362 and R^2 = 0.131, was not refuted by the results of the statistical analyses. This finding indicates that the pursuit of financial knowledge is positively related to one's behavioral profile (Chetty, 2015; Schilbach et al., 2016; Wakita et al., 2000). Bolder, risk-taking people tend to seek out more financial information than those who are more detached with their finances (Lloyd & Friedland, 2016). The more prone to taking risks, the more they seek out information, improving how they handle their resources (Hamilton & Morgan, 2018). Conversely, the more conservative tend to be more resistant with banking and using banking services, even avoiding seeking to improve their knowledge of finance.

Finally, we have the intention to borrow. This intention is little influenced by the behavioral profile, H6, with $\beta = 0.108$ and $R^2 = 0.012$, even though its result is significant for a p-value of 5%. The intention to borrow for low-income citizens is much more linked to other factors than their behavioral profile (Hamilton & Morgan, 2018). This is because much of the borrowing is linked to personal or household budget imbalance, which causes restriction of the possibility of consumption (Botti et al., 2008; Cannon et al., 2018; Chen & Miller, 2012; Kraus et al., 2009; Shah et al., 2012) and not to productive investments (Bernheim et al., 2015; Bertrand et al., 2006; Botti et al., 2008; Dupas & Robinson, 2009). Thus, this finding confirms the theoretical issues already pointed out in the literature review.

CONCLUSION

Our study sought to identify how the behavioral profile of citizens from low-income populations influences banking and how these citizens deal with the banking services offered and saving for future expenses. Identifying the scarce number of studies with this objective and pointing to the importance of financial inclusion, we observed a gap in identifying skills that can improve the financial inclusion of the low-income population (Friedland et al., 2012; Lloyd & Friedland, 2016). Thus, we addressed our research question, "what is the influence of behavioral profile on the various elements that improve financial citizenship?" To answer this question, we used behavioral theory through the 3M Model (Mowen, 2000; Asebedo et al., 2018), which seeks to identify the influence of individuals' various psychological characteristics on their actions and reactions to consumption.

The method used, quantitative survey research, sought to capture how these elements interact and create resistance to technology for banking, more or less banking through the amount of use, more or less intention to use the banking services offered, more or less acquisition of knowledge about finance and how all these elements influence the intention to save and the consumption profile. We analyzed the survey using SEM-CB and identified that the behavioral profile greatly impacts the risk profile and influences the constructs studied. All the hypotheses we tested were supported by the statistical results, proving that the Behavioral profile influences both the adoption of technologies to access banking services, such as having or not having a bank account and its frequency of use and the access to banking services, such as saving and searching for financial information. This finding indicates that more conservative people have greater resistance to the adoption of technology, banking, access to banking services, formal savings, and the adoption of financial information, on the other hand, more daring people, who take more risks, have less resistance to the adoption of technologies to access bank accounts, less resistance to open an account and its use, less resistance to the use of banking services, less resistance to the adoption of formal savings and the adoption of financial knowledge.

The main theoretical contribution of this study was to adapt the 3M behavioral theory (Mowen, 2000) to the reality of developing countries, especially Brazil, improving the understanding of the influence of this behavioral profile on the elements that facilitate financial citizenship as defined by BCB (Corrieri & Correia, 2020). The practical contribution is the proof that Skills, as a Behavioral profile, influence the resistance to banking and its related elements, pointing to both banks and governments ways to improve the inclusion of low-income citizens via adaptation of services, explanations, and public policies aimed at this group of citizens.

The limitations of this study were the use of poorly tested indicators for the identification of the constructs studied. In addition to this limitation, it would be important to verify if these studied elements are necessary for banking to occur and if other elements should be considered for the results to happen (Dul, 2016).

We suggest that further research be conducted in the post-pandemic of COVID-19 to identify its impact on the bankability of the low-income population. We also suggest that this research be conducted again with other measurement scales to improve and deepen this relevant topic. Finally, we suggest that qualitative research be carried out to identify people's behaviors from low-income social classes concerning banking or resistance.

REFERENCES

Albuquerque, J. P., Diniz, E. H., & Cernev, A. K. (2016). Mobile payments: a scoping study of the literature and issues for future research. *Information Development*, 32(3), 527-553.

Alkhowaiter, W. A. (2020). Digital payment and banking adoption research in Gulf countries: A systematic literature review. International Journal of Information Management, 53, 1-17.

Allen, F., Demirguc-Kunt, A., Klapper, L., & Martinez Peria, M. S. (2016). The foundations of financial inclusion: Understanding ownership and use of formal accounts. *Journal of Financial Intermediation*, 27, 1–30.

Asebedo, S. D. (2018). Personality and Financial Behavior. In Client Psychology, edited by Charles Chaffin (137-151), CFP Board, Hoboken, NJ: John Wiley & Sons.

Asebedo, S. D., Wilmarth, M. J., Seay, M. C., Archuleta, K., Brase, G. L., & MasDonald, M. (2018) Personality and Saving Behavior among Older Adults. *The Journal of Consumer Affairs*, 53, 488-519.

Bagozzi, R. P. & Yi, Y. (1988). On the evaluation of structural equation models. Journal of the Academy of Marketing Science, 16(1), 74-94. doi:10.1177/009207038801600107

Bentler, P. M. (1990) Comparative fit indexes in structural models. Psychological Bulletin, 107(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Bentler, P. M. & Bonett, D. G. (1980) Significance test and goodness of fit in the analysis of covariance structures. Psychological Bulletin, 88(3), 588-606.

Bernheim, B. D., Ray, D. & Yeltekin, S. (2015). Poverty and Self-Control. *Econometrica*, 83(5): 1877-1911.

Bertrand, M., Mullainathan, S. & Shafir, E. (2006). Behavioral Economics and Marketing in Aid of Decision Making Among the Poor. Journal of Public Policy & Marketing, 25(1), 8-23.

Botti, S., Broniarczyk, S., Häubl, G., Hill, R., Huang, Y., Kahn, B., Kopalle, P., Lehmann D., Urbany, J. & Wansink, B. (2008). Choice under restrictions. Marketing Letters, 19(3/4), 183-199.

Bryman, A. (2012) Social Research Methods. 4 ed., New York: Oxford University Press.

Cannon, C., Goldsmith, K. & Roux, C. (2018). A self-regulatory model of resource scarcity. Journal of Consumer Psychology, 29, 104-127.

Carrieri, Q. de P. & Correia, G. F. A. (2020) Estudos Organizacionais no Brasil: Construindo Acesso ou Replicando Exclusão? *Revista de Administração de Empresas – RAE*, 60(1), 59-63.

Carvalho, L.S., Meier, S., & Wang, S.W. (2016). Poverty and economic decision-making: Evidence from changes in financial resources at payday. American Economic Review, 106(2), 260–284.

Chen, M. & Miller, D. (2012). Shift-and-Persist Strategies: Why Low Socioeconomic Status Isn't Always Bad for Health. Perspectives on Psychological Science, 7(2), 135-158.

Chetty, R. (2015). Behavioral economics and public policy: A pragmatic perspective. American Economic Review, 105(5), 1–33.

Chibango, C. (2014), "Mobile money revolution: an opportunity for financial inclusion in Africa". *The International Journal of Humanities & Social Studies*, Vol. 2 No. 2, pp. 59-67.

Brasil, (1988) Constituição da República Federativa do Brasil de 1988. Brasília. Recovered on 24 May 2021, from http://www.planalto.gov.br/ccivil_03/constituicao/constituicao.htm

Costa, P. T., Jr., & McCrae, R. R. (1992) NEO-PI-R: Professional Manual. Odessa, FL: Psychological Assessment Resources.

Cunliffe, A. L. (2010) Crafting Qualitative Research: Morgan and Smircich 30 Years On. Organization Research Methods, 000(00), 1-27.

Diamantopoulos, A., Riefler, P. & Roth, K. P. (2007) Advancing formative measurement models. Journal Business Research, 61(2008), 1203 – 1218.

Davis, M. (2002), Late Victorian Holocausts: El Niño Famines and the Making of the Third World, *Verso*, London, 529.

Davis, K., & Runyan, R. C. (2016) Personality Traits and Financial Satisfaction: Investigation of a Hierarchical Approach. *Journal of Financial Counseling and Planning*, 27 (1): 47-60.

Dul, J. (2016) Necessary Condition Analysis (NCA): Logic and Methodology of "Necessary but not Sufficient" Causality. *Organizational Research Methods*, 19(1), 10-52.

Dupas, P., & J. Robinson. (2009). Savings Constraints and Microenterprise Development: Evidence from a Field Experiment in Kenya. National Bureau of Economic Research Working Paper 14693. Consulting in: https://www.nber.org/papers/w14693.

Fernbach, P. M., Kan, C., & Lynch, J. G., Jr. (2015). Squeezed: Coping with constraint through efficiency and prioritization. Journal of Consumer Research, 41(5), 1204-1227.

Ferrari, A. (2012). Digital Competence in practice: an analysis of frameworks. Luxembourg: Publications Office of the European Union. DOI: 10.2791/82116.

Fornell, C., & Larcker, D. (1981). Structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.

Friedland, L. A., Napoli, P., Ognyanova, K., Weil, C. & Wilson, E. J. III (2012). Review of the literature regarding critical information needs of the American public. Washington, DC: Federal Communications Commission. Retrieved from http://transition.fcc.gov/bureaus/ocbo/Final_Literature_Review.pdf

Fuller, C. M., Simmering, M. J., Atinc, G., Ainc, Y. & Babin, B. J. (2015) Common methods Variance Detection in Business Research. Journal of Business Research. 000(0). dx.doi.org/10.1016/j.jbusres.2015.12.008

Gerhard, P., Gladstone, J. J., & Hoffmann, A. O. I. (2018). Psychological characteristics and household savings behavior: The importance of accounting for latent heterogeneity. *Journal of Economic Behavior & Organization*, 148, 66–82.

Gonzalez, L. (2020), "Blockchain, herding, and trust in peer-to-peer lending", *Managerial Finance*, 46(6), 815-831

Gudergan, S. P., Ringle, C. M., Wende, S. & Will, A. (2007) Confirmatory tetrad analysis in PLS path modeling. Journal Business Research, 61(2008), 1238 – 1249.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate Data Analysis (7th Edition). NJ: Prentice-Hall

Hair, J. F., Ringle, C. M., and Sarstedt, M. (2011). "PLS-SEM: Indeed a Silver Bullet." Journal of Marketing Theory and Practice 19 (2): 139-151.

Hair, J. F., Gabriel, M. L. D. S., Patel, V. K. (2014). Amos Covariance-Based Structural Equation Modeling (Cb-Sem): Guidelines on Its Application as a Marketing Research Tool. Brazilian Journal of Marketing - BJM, 13(2), 44-55.

Hamilton, J. T. & Morgan, F. (2018) Poor information: How Economics Affects the Information Lives of Low-income Individuals. International Journal of Communication, 12(2018), 2832-2850.

Hamilton, R.W., Mittal, C., Shah, A., Thompson, D.V., and Griskevicius, V. (2019), How Financial Constraints Influence Consumer Behavior: An Integrative Framework. J Consum Psychol, 29: 285-305.

Harman, H. H. (1976). Modern factor analysis, 3rd ed. Chicago, IL: The Un. of Chicago Press.

Haushofer, J. & Fehr, E. (2014). On the Psychology of Poverty. Science, 344(6186), 862–867.

Jadlow, J. W. & Mowen, J. C. (2010) Comparing the Traits of Stock Market Investors and Gamblers. *Journal of Behavioral Finance*, 11 (2): 67-81.

Jeanneney, S. G. & Kpodar, K. (2011) Financial Development and Poverty Reduction: Can There be a Benefit without a Cost? Journal of Development Studies, 47(1), 143–163.

Jöreskog, K. G., and Wold, H. O. A. (1982). "The ML and PLS Techniques For Modeling with Latent Variables: Historical and Comparative Aspects." In Systems Under Indirect Observation, Part I. Eds. H. O. A. Wold and K. G. Jöreskog. Amsterdam: North-Holland, 263-270.

Kang, J. Y. M., & Johnson, K. K. P. (2015) F-Commerce Platform for Apparel Online Social Shopping: Testing Mowen's 3M Model. *International Journal of Information Management*, 35 (6): 691-701.

Kim, M., Zoo, H., Lee, H., & Kang, J. (2018). Mobile financial services, financial inclusion, and development: A systematic review of academic literature. *The Electronic Journal of Information Systems in Developing Countries*, *84(*5), e12044.

Kraus, M. W., Piff P. K., Keltner D. (2009). Social class, sense of control, and social explanation. Journal of Personality and Social Psychology, 97 (6), 992–1004.

Lal, Taesem. (2018) Impact of Finacial Inclusion on Poverty Alleviation Through Cooperative Bancks. *International Journal of Social Economics*, 45(5), 808-828.

Ligon, E., Malick, B., Sheth, K., & Trachtman, C. (2019). What explains the low adoption of digital payment technologies? Evidence from small-scale merchants in Jaipur, India. PloS one, 14(7), e0219450.

Lloyd, M., & Friedland, L. A. (2016). The communication crisis in America, and how to fix it. New York, NY: Palgrave Macmillan.

Malhotra, N. H., Nunan, D. & Birks, D. F. (2017) Marketing Research: An Applied Approach. 5ª ed., Edinburgh/UK, Perarson.

Mardia, K. V. (1980) 9 Test of Univariate and Multivariate Normality. Handbook of Statistics, 1, 279 – 320.

Mosca, I. & McCrory, C. (2016). Personality and Wealth Accumulation among Older Couples: Do Dispositional Characteristics Pay Dividends? Journal of Economic Psychology, 56 (October), 1-19.

Mowen, J. C. (2000). The 3M Model of Motivation and Personality: Theory and Empirical Applications to Consumer Behavior. Norwell, MA: Kluwer Academic Publishers.

Mowen, J. C., Fang, X. & Scott, K. (2009). A Hierarchical Model Approach for Identifying the Trait Antecedents of General Gambling Propensity and of Four Gambling-Related Genres. *Journal of Business Research*, 62(12), 1262-1268.

Mullainathan, S., & Shafir, E. (2013). Scarcity: Why having too little means so much. New York: Henry Holt and Company.

Napoli, P. M., & Obar, J. A. (2014). The emerging mobile Internet underclass: A critique of mobile Internet access. *The Information Society*, 30(5), 323-334.

Nunnally, J. C. & Bernstein, I. (1994) Psychometric theory, 3ª ed., New York: McGraw-Hill.

Patil, P. P., Dwivedi, Y. K., & Rana, N. P. (2017, November). Digital payments adoption: an analysis of literature. Lecture Notes in Computer Science (LNCS 10595). Springer International Publishing, p. 61-70.

Pazarbasioglu, C., Mora, A. G., Uttamchandani, M., Natarajan, H., Feyen, E., & Saal, M. (2020). Digital Financial Services. Washington, DC: World Bank.

Pedhazur, E. J. & Schmelkin, L. P. (1991) Measurement, Design, and Analysis: An Integrated Approach. Lawrence Erlbaum Associates: Hillsdale, New Jersey, EUA.

Podsakoff, P. M., MacKenzie, S. B., Podsakoff, N. P., & Lee, J.-Y. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903.

Podsakoff, P. M., MacKenzie, S. B. & Podsakoff, N. P. (2012) Sources of Method Bias in Social Science Research and Recommendations on How to Control It. Annual Review Psychology. 63, 539-569.

Popper, K. R. (2008) *The logic of scientific research.* 16th ed. Translate: L. Hegenberg, O. S. Mota, São Paulo: Cultrix.

Reinartz, W. J., Haenlein, M., & Henseler, J. (2009). "An Empirical Comparison of the Efficacy of Covariance-Based and Variance-Based SEM." International Journal of Research in Marketing 26 (4): 332-344.

Ringle, C., Silva, D., & Bido, D. S. (2014). Modelagem de Equações Estruturais com utilização do Smartpls. Revista Brasileira de Marketing, 13(2), 54-71.

Sela, V. M., Gonzalez, L. & Christopoulos, T. P. (2020) Costruction of Finacial Inclusion Agenda in Light of the Actor-Networking Theory. *Revista de Administração Pública – RAP*. 54(1), 162-180

Schilbach, F., Schofield, H., & Mullainathan, S. (2016). The psychological lives of the poor. American Economic Review, 106(5), 435–440.

Shah, A. K., Mullainathan, S., & Shafir, E. (2012). Some consequences of having too little. *Science*, 338(6107), 682-685.

Sotomayor, O. (2021) Pobreza, escolaridade e distribuição de renda no Brasil. *Nexo Journal*, Recovered on 24 May 2021, from https://www.nexojornal.com.br/ensaio/2021/Pobreza-escolaridade-e-distribui%C3%A7%C3%A3o-de-renda-no-Brasil

Tabachnick, B.G. & Fidell, L.S. (2013) Using Multivariate Statistics, 6ª ed., New York, NY: Pearson.

Van Deursen, A., & Van Dijk, J. (2019). The first-level digital divide shifts from inequalities in physical access to inequalities in material access. New Media & Society, 21(2), 354-375.

Van Dijk, J., & Van Deursen, A. (2014). Digital skills: unlocking the Information Society. London: Palgrave Macmillan

Venkatesh, V.; Morris, M.; Davis, G.; Davis, F. D. (2003) User acceptance of information technology: toward a unified view. *MIS Quarterly*, 27(3), pp.425-478.

Venkatesh, V., Thong, J., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association Information System*, 17, 328-376.

Wakita, S., Fitzsimmons, V. S. & Liao, T. F. (2000). Wealth: Determinants of Savings Net Worth and Housing Net Worth of Pre-Retired Households. *Journal of Family and Economic Issues*, 21(4): 387-418.

Whetten, D. A. (1989) What Constitutes a Theoretical Contribution? Academy of Management Review, 14(4), 490-495.