

Correa, Juan C.; Dakduk, Silvana; van der Woude, David; Sandoval-Escobar, Marithza; Lopez-Llamas, Rafael

Article

Low-income consumers' disposition to use automated banking services

Cogent Business & Management

Provided in Cooperation with:

Taylor & Francis Group

Suggested Citation: Correa, Juan C.; Dakduk, Silvana; van der Woude, David; Sandoval-Escobar, Marithza; Lopez-Llamas, Rafael (2022) : Low-income consumers' disposition to use automated banking services, Cogent Business & Management, ISSN 2331-1975, Taylor & Francis, Abingdon, Vol. 9, Iss. 1, pp. 1-20,
<https://doi.org/10.1080/23311975.2022.2071099>

This Version is available at:

<https://hdl.handle.net/10419/288775>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/4.0/>

Low-income consumers' disposition to use automated banking services

Juan C. Correa, Silvana Dakduk, David van der Woude, Marithza Sandoval-Escobar & Rafael Lopez-Llamas

To cite this article: Juan C. Correa, Silvana Dakduk, David van der Woude, Marithza Sandoval-Escobar & Rafael Lopez-Llamas (2022) Low-income consumers' disposition to use automated banking services, Cogent Business & Management, 9:1, 2071099, DOI: [10.1080/23311975.2022.2071099](https://doi.org/10.1080/23311975.2022.2071099)

To link to this article: <https://doi.org/10.1080/23311975.2022.2071099>



© 2022 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.



[View supplementary material](#)



Published online: 17 May 2022.



[Submit your article to this journal](#)



Article views: 1824



[View related articles](#)



[View Crossmark data](#)



Citing articles: 4 [View citing articles](#)



Received: 26 January 2022
Accepted: 15 March 2022

*Corresponding author: Juan C. Correa, CESA Business School, Colegio de Estudios Superiores de Administración-CESA, Casa Echavarría - Diagonal 34 # 5A-23 Tercer Piso, Bogotá, Colombia
E-mail: juan.correan@cesa.edu.co

Reviewing editor:
Albert W. K. Tan, Asia Pacific Graduate Institute, Shanghai Jiao Tong University, Singapore

Additional information is available at the end of the article

OPERATIONS, INFORMATION & TECHNOLOGY | RESEARCH ARTICLE

Low-income consumers' disposition to use automated banking services

Juan C. Correa^{1*}, Silvana Dakduk², David van der Woude², Marithza Sandoval-Escobar³ and Rafael Lopez-Llamas²

Abstract: Automated banking services rely on the so-called fintech technologies. These technologies, however, represent an opportunity to enhance financial inclusion indicators among low-income customers. This paper aims to develop a new conceptual framework to analyse low-income consumers' disposition to use automated banking services. The work consists of an omnibus study conducted in eight major cities of Colombia. A survey aiming to measure the disposition to use automated banking services as a function of technology disposition provided by bank firms was developed and validated with a sample of 483 Colombian low-income residents. An exploratory analysis was applied, estimating items variance and covariance matrices. Sampling adequacy and assumption evaluation were evaluated through the Kaiser-Meyer-Olkin test, Tau-equivalence test, and homogeneous items test. Robust parameters were estimated via Structural Equation Modelling following the standards of reproducible research. Statistical, robust, and significant relationships between technology disposition and use of automated banking services in low-income Colombian consumers were confirmed, suggesting the potential

ABOUT THE AUTHOR

Juan C. Correa holds a PhD in Science, Professor-Researcher at CESA Business School. His interests focus on behavioral data science.

Silvana Dakduk holds a PhD in Consumer and Economic Psychology. She is a professor of marketing at Los Andes. Her publications and research interests relate to consumer behavior, technology adoption, and technology-based pedagogical innovation.

David van der Woude is a PhD candidate in consumer psychology. He is a professor of marketing at the CESA Business School in Bogotá, Colombia. His publications are related to consumer behaviour and technology adoption.

Marithza Cecilia Sandoval-Escobar holds an EdD and a Master in Consumer Psychology. Her publications and research interests are related to behavioural economics, brand analysis, and the use of the BPM. She is also the editor of the *Journal Suma Psicológica*.

Rafael Lopez is an adjunct professor in marketing research and marketing strategies. He is the founder of the market research firm, Brandstrat, and a regular columnist in business newspapers.

PUBLIC INTEREST STATEMENT

Are bank innovations a good bet for financial inclusion purposes? This paper provides fresh insights into why Colombian financial institutions might benefit from reaching out to more low-income consumers. With the application of a robust methodological approach, we confirmed the potential success of deploying these innovative services to boost financial inclusion in Colombian citizens. This result is significant given the current concern for the Colombian government and other emerging economies in Latin America on how to create an inclusive model to make financial services more dynamic and in reach for low-income users. A contribution of automation in banking services is that they will reduce the costs in the middle and long term and improve accessibility to a typically ignored customer base.

success of deploying these services as a means to boost financial inclusion in this segment. This study provides fresh conceptual insights on low-income customers' disposition to adopt and use ever-changing technologies for the financial and banking sector. It is among the first empirical studies that provide empirical evidence that breaks the stereotype that low-income customers are reluctant to use new technologies in the financial sector.

Subjects: Consumption; Consumer Behaviour; Applied Social Psychology; Social Psychology of Organizations; Consumer Psychology; Economic Psychology

Keywords: Automation; banking services; financial inclusion; low-income consumers; technology disposition

1. Introduction

What drives low-income customers to use automated banking services? This is one of the most important questions many financial and banking firms share in a post-pandemic era where economic reactivation is essential. To provide a meaningful framework for this question, it is worth mentioning the growing interest in multiplying the access to financial services in all countries (Jonker et al., 2020), and particularly for emerging economies (Akhter et al., 2020; Mogaji et al., 2021). In developing countries, financial inclusion is a key mechanism for banks to reach more people (Sithole et al., 2021). Roughly speaking, financial inclusion relates to the access and availability of the formal financial system to all the sections of society (Rastogi & Ragabiruntha, 2018), and includes issues such as helping people better manage their resources and improving financial capabilities (Arun & Kamath, 2015; Mhlanga, 2021). Initiatives aiming at including more people in financial services do not take place in a vacuum. Instead, these initiatives occur in an ecosystem of innovative services. Online payment systems (Teo et al., 2015), M-bank (Albashrawi & Yu, 2020), Internet banking (Liao et al., 2016) or sustainable banking (Mejía-Escobar et al., 2020) are just a few exemplars of innovation in the financial sector. Given that these new functionalities might also be difficult to adopt for bank users (Akhter et al., 2020), the introduction of these technologies posits several challenges for scholars and practitioners. Particularly if they want to attract larger segments who accept and use these services. For example, a recent study identified how the fear of the COVID-19 pandemic and social distancing acted as factors inducing customers to choose cashless payments (Huterska et al., 2021). Note that in this latter case, an external event (i.e., the pandemic) and not the institutional efforts done by banks was the trigger that promoted a change in the way bank users interact with fintech developments.

According to Sunderaraman et al. (2020), the study of consumer behaviour in the financial context does not accurately describe the actual conduct. One reason that supports this statement is digital transformation. Such a transformation includes but is not limited to the growing use of mobile devices with an Internet connection. With these tools, users belong to one of the following mutually exclusive categories: either they belong to the so-called "early adopters" or not (Ratten & Ratten, 2007). Early adopters (also known as innovators) tend to belong to younger demographic age groups, and they are more prone to adopt and use technologies without hesitation. Users that do not fit in the profile of early adopters tend to be more distant from adopting or using technology-mediated banking services. Empirical evidence from non-developed countries like Ethiopia, for example, supports this broad categorisation (Alemu et al., 2015). A limitation of this empirical yet simplistic conception of bank users is that it fails to explain consumers' willingness to follow, adopt, and use ever-changing fintech developments.

Indeed, if age were the only responsible factor driving the adoption and use of fintech developments, other efforts would not exist to understand effective technology adoption mechanisms. In this context, the automation of financial services is deemed another driving mechanism, which might become the most effective way of overcoming traditional barriers to including a more

diverse client base (Mushtaq & Bruneau, 2019). Here, insights from “disruptive innovations in low-income markets” (Da Costa Nogami & Veloso, 2017) might reveal novel ways to understand the challenges for financial inclusion of low-income consumers and leverage these technology-mediated banking services. Nonetheless, theoretical developments on the relationship between automation of financial services and consumers’ willingness to adopt and use these services are far from being well documented in the literature. This gap offers exciting opportunities for contributing to financial and banking firms. This is particularly true for strategic implementations purposes in the sector, which is a recognised gap in the literature (Alemu et al., 2015; Meyer et al., 2020; Shareef et al., 2018).

Existent reviews on technology adoption highlight two elements. The first one is the theoretical approach employed. Most empirical studies rely on “technology acceptance model” (TAM), initially proposed by Davis (1986) and the “user acceptance of information technology” (UTAUT), proposed by Venkatesh et al. (2003). In a recent review, Souiden et al. (2021) have pinpointed that these frameworks “have locked the door on the emergence of other theories that can enrich the discipline” (p. 233). This circumstance leads to another common characteristic of empirical studies. Most of them seem dogmatic; they follow a uniform structure regarding the contents derived from these theoretical lenses. In this regard, Souiden et al. (2021) went even further and claimed their agreement with Benbasat and Barki (2007) who regarded that such a conceptualisation “has led to the creation of an illusion of progress in knowledge accumulation” (p. 212). We regard this statement as a call for developing fresh insights relying on other conceptualisations. Apart from these ideas, empirical studies tend to focus on developed countries (Fernández-Olit et al., 2019) with general samples, ignoring or minimising the relevance of low-income consumers who belong to the most representative sector in emerging economies (Kaplinsky et al., 2009; Mohan & Potnis, 2017). As a result, most business innovations target middle and upper-class consumers in developed countries. From this data-driven perspective, the novelty of our study is evident as it focuses on low-income consumers from Colombia, a developing country in South America.

As per Yurdakul et al. (2017), marketing practitioners have neglected the conceptualisation of the low-income consumer segment. As a token of this, it is worth mentioning the interest in low-income marketing illustrated in the bestseller titled *The Fortune at the Bottom of the Pyramid* by Prahalad and Prahalad (2005). In marketing, the low-income consumer is a broad category. It describes the people that belong to the societal group with limited incomes. This group represents the majority of the population in emerging economies. Despite the size of this group, there is a lack of consensus on who low-income consumers are. The definition of low-income consumers often depends on the official definition of the poverty level, which varies across nations and political criteria. Above and beyond these differences, however, the term low-income refers to when monetary means do not satisfy basic needs and as well have limited access to essential public services (Tarafdar et al., 2012).

According to Coppack et al. (2015), low-income consumers are vulnerable, highly susceptible to harsh circumstances. Such a vulnerability derives from demographic, economic, psychological, and social dimensions (Ali & Subramanian, 2022). A recent study shows that financial skill and behaviour contribute the most to well-being for vulnerable consumers (Xiao & Porto, 2021). Nudging low-income consumers to follow sensible financial behaviour is more important than teaching them financial knowledge and skills.

The idea of inclusive business models is deeply rooted in promising digital developments aiming to meet the needs of low-income consumers (Hamilton & Catterall, 2005). Dakduk et al. (2020) show several successful experiences of financial and banking firms that funded initiatives for low-income consumers. Initiatives of this sort include, among others, Grameen Bank in India (Hart & Christensen, 2002), Banesco Banca Comunitaria in Venezuela (Auletta et al., 2019), M-Pesa in Kenya (Wenner et al., 2018), G-Cash in the Philippines (Pelletier et al., 2019), Nequi in Colombia (Agidi, 2018), Swazi MTN in Eswatini (Myeni et al., 2020), WIZZIT and MTN Mobile Money in South

Africa and CELPAY in Zambia (Andrianaivo & Kpodar, 2012). These experiences show how technology-mediated services in low-income consumers can boost financial inclusion. These outcomes are in line with previous research pinpointing the relationship between financial inclusion and economic development and how increased investment provides lucrative opportunities for entrepreneurs, promoting positive financial behaviour (Karjaluo et al., 2019; Shareef et al., 2018).

2. Understanding consumers' disposition to use automated banking services

As per Global Microscope 2019 Unit (2019), financial inclusion has significantly increased in recent years, and specifically in Latin America. Despite this increment in the last decade, this growth is disconnected from developing the population's digital skills to use virtual financial products effectively. From this viewpoint, it is reasonable to assume that technology use might be one of the most fundamental factors that explain consumers' disposition to use automated banking services, especially in women and countries with inadequate massive Internet coverage and access to digital channels. These last set of factors are undoubtedly important. They belong to the infrastructural reality incumbent on public governments. Once this infrastructure is enhanced via public or private investment, consumers' adoption and use of technology should increase. An open question that derives from this insight is the increased size due to infrastructure enhancements and the increment due to financial and bank efforts developed thanks to these infrastructural enhancements.

The financial services automation process is the future for the banking sector. Automation occurs when technology contributes to the complete production or delivery of goods and services in part or without direct human interaction (Foster & Rhoden, 2020). This type of commercial operation requires autonomy by the consumer and a new perspective from the banking sector. This new perspective, in turn, demands a clear definition and differentiation of the functions still conducted by employees from those conducted by automated technologies and the resulting human-machine interaction that did not exist before. With these innovative changes, consumers might see and interpret a radically different organisational context against their previous experiences. First, the consumer may prefer to interact with humans.

In contrast, financial services based on automated technology-mediated resources require a customer-centred or market-oriented approach to assure that customers are comfortable using these services, thus increasing usage (Camarero, 2007). Second, automation can promote the development of a scalable business model adequate for financial inclusion strategies. Third, the automation process should be aligned with the customer journey in banking services because it should include the different touchpoints to attract and convert new customers into active users (Verkijika, 2020). Thus, it becomes vital to understand these factors as technology disposition that firms can consider for financial inclusion purposes in developing countries where low-income consumers represent most of the population.

In the banking industry, automation plays various roles in different services and stages of financial transactions. Most common automation applications relate to the channel strategy and increased efficiency in customer service relationships by deploying and using ATMs, SMS, websites, call centres, and mobile applications. These applications are strategically targeted to current clients to promote the transaction behaviour conveniently. Nonetheless, the automation that attracts new customers is not in the same development stage. For example, Artificial Intelligence (AI) and big data have been used to create new services for product recommendation and customer assistance (Met et al., 2020).

Nonetheless, these technologies are far from being unquestionable from an ethical point of view. A recent example of this type of innovation is the work in progress of Beccalli et al. (2020), who have been exploring the ethical dilemmas related to AI use in financial portfolio management and their managerial implications. Apart from the uses mentioned above of automation, they all increase service coverage, allowing different segments to benefit from the financial sector.

The advantages of automation in the banking sector are aligned with the most cited barrier to serving low-income customers (D'Andrea & Stengel, 2004). A challenge to success in this sector is developing a business model that can attract large-scale economies. This business model should go hand-in-hand with the new perspective of the banking sector previously described. In other words, by differentiating which tasks are done by employees from those exerted by automated technologies, banks will be able to define how customers should interact with these innovations. Moreover, this supposes less investment in physical infrastructure (e.g., reducing the number of branch offices) at the expense of a significant investment in software development, an advantage in several dimensions.

On the one hand, low-income customers will see no need to invest their time and money in visiting branch offices, because they could receive the same service wherever they are. This is an obvious advantage as it helps avoid unfriendly bank policies, procedures, and unwelcoming staff behaviour that can prevent the typical experience when accessing essential banking services (Kamran & Uusitalo, 2019). On the other hand, banks will also redefine the scope of security services for cash management logistics (e.g., cash withdrawals in ATMs could be replaced by electronic transfers that the customer receives into the bank account using a smartphone with an installed app).

As a result of these efforts, banks will become an external incentive for low-income customers to increase or improve their digital literacy with mobile phone use (Morgan & Long, 2020). In this way, customers will need to engage with the dynamics of apps updates and upgrades and get familiarised with the subtle differences that emerge when it comes to using a smartphone, a tablet, a computer, or interacting with virtual employees through call centres. This futuristic vision is aligned with the role of automation and labour force participation in modern societies (Grigoli et al., 2020). Although everything seems to pinpoint the positive impact of these innovations on the sector, managers and business leaders are called to have a better understanding of how to make these benefits tangible or concrete (Y. Zhou & Tyers, 2019). Leaders in this sector are essential catalysts driving a large-scale adoption by consumers.

If financial inclusion is deemed the ultimate goal of banking firms, then the evaluation of low-income customers' disposition to use automated banking services becomes the critical factor of a successful strategy aiming to contribute to prosperity diffusion in the most vulnerable segments in emerging economies (Ramírez-Correa et al., 2020).

However, although the scientific literature has shown a growing interest in technology adoption and this consumer segment, there is little research linking these two. Although carried out in emerging economies, research on technology adoption has focused mainly on young people, existing bank users, or those with banking potential. In a recent literature review developed by Ashique and Subramanian (2022) analysed 79 publications on the evolution of Mobile Banking adoption in the last two decades. Among their findings they reveal that although more than 70% of research has been conducted in developing countries none of these studies evaluated low-income consumers. Similarly, Chauhan et al. (2022) evaluated 88 papers between 2001 and 2021 on customer experience in digital banking and reported no explicit evidence of empirical efforts in emerging economies.

In another review focusing on 102 publications between 2008 and 2020, Pandey et al. (2022) confirms that low-income consumers are willing to adopt new mobile technologies and regarded it as a means to improve their quality of life. Nevertheless, for this adoption to take place, firms should develop specific innovations that match their digital maturity and technological resources. Along with these endeavours, firms should also offer inputs for using banking platforms.

Given the relevance of generating knowledge that effectively promotes financial inclusion, the contribution of the current study consists of providing new empirical evidence on this matter by

analysing low-income customers residing in eight major cities of Colombia, and this might be regarded as an extension of previous conceptual efforts (Thoene & Turriago-Hoyos, 2017). This developing country in South America is a member of the Organisation for Economic Co-operation and Development (OECD) and still presents several barriers that prevent people from using online banking services, according to local reports of Asobancaria, the professional network for financial and banking firms in Colombia.

According to financial inclusion reports from 2020, even though 87.8% of Colombians have access to financial services (Superintendencia financiera, 2020), one of the first challenges is how the industry can attract new customers and maintain them active. Put it differently, for the Colombian government and other emerging economies in Latin America, this challenge relates to creating an inclusive model to make financial services more dynamic and in reach for low-income users. A contribution of automation in banking services is that they will reduce the costs in the middle and long term and improve accessibility to a typically ignored customer base.

3. Research method

This study uses several references related to the Technology Acceptance Model (TAM) and the extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT2) model, which has demonstrated efficiency in previous research to determine the level of technology disposition to support this research (Tamilmani et al., 2021; Venkatesh et al., 2012, 2016). Based on this methodological approach, the data was collected using a questionnaire as an instrument of this research. The instrument was developed following the multi-stage approach suggested by (Morgan-Thomas & Veloutsou, 2013). The first items rely on a thorough literature review and resulted in a questionnaire with two sections demographic information and the items themselves. The items and scales were adapted from previous research with preliminary reliability and validity metrics providing evidence on these constructs. Each item was measured with a 7-point Likert scale, ranging from “strongly disagree” (1) to “strongly agree” (7).

The development of the questionnaire and the fieldwork was carried out in partnership with Brandstrat. This Colombian market research firm carried out a syndicated, omnibus study sponsored by financial institutions to evaluate Colombian consumers’ habits, usage, and expectations in financial services. In alliance with the CESA School of Business in Bogotá, Colombia, the measure and analysis conducted from February to March of 2020 incorporated the disposition to adopt financial services among low-income customers in order to make synergy with an academic and practitioner perspective and based on the relevant perspective on automation to build a successful inclusion strategy.

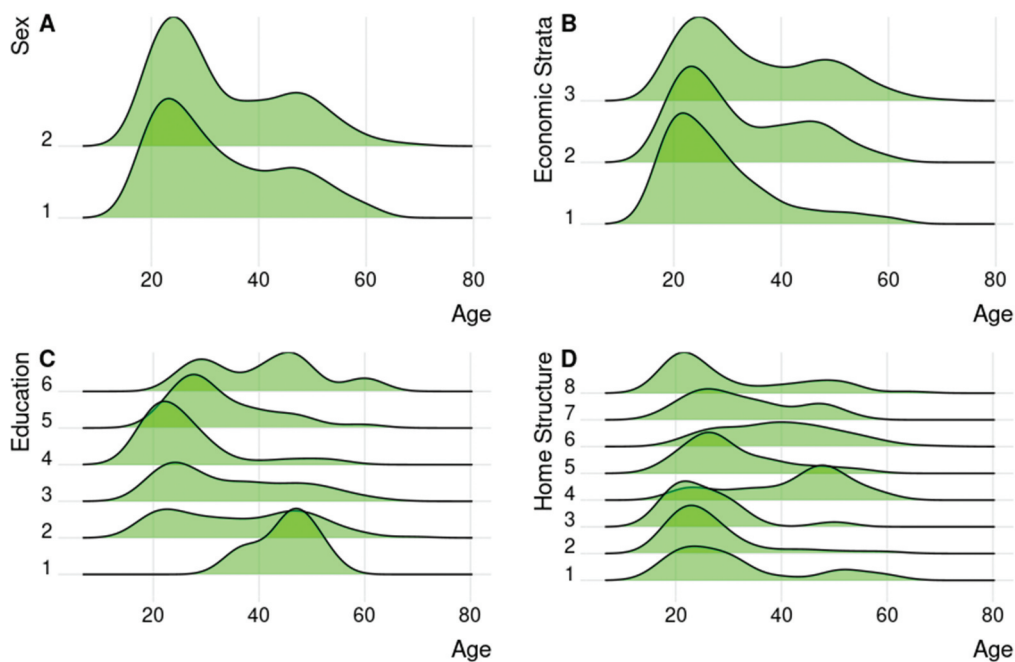
The study used an online panel. Given that the study was syndicated market research, the sample was selected by random sampling proportional to demographic factors of the overall population in Colombia (i.e., gender, age, educational level). Furthermore, the sampling procedure included eight largest cities (i.e., Bogotá, Cali, Medellín, Barranquilla, Bucaramanga, Manizales, Cartagena and Pereira). The minimum age of participants was 18, and they all reported themselves as possessing a traditional banking or fintech service with at least three months of continuous use before the survey.

This research took six weeks to collect data and obtained 483 respondents through the questionnaire. The data analysis technique used in this research was conducted in two phases. First, measurement properties of our two principal constructs to evaluate the questionnaire and sample adequacy. Subsequently, this study used SEM (Structural Equation Modeling) to estimate the relationship between variables in the model using the lavaan package in R.

3.1. Sample description

A total of 483 individuals residing in eight cities of Colombia participated in the study. To be included in the study, subjects signed up an informed consent that described both the purpose of the investigation and its confidential treatment of the data. All participants (female = 248,

Figure 1. Statistical distributions of participants.



male = 230, aged between 18 and 69 years old) responded to a series of questions in order to characterise the household's socioeconomic conditions as follows. Participants reported that their monthly income was equal to or lower than two minimum local salaries (i.e., around 250 US\$). People with this income represent the lower-to-middle class in the country, and their stratum is classified as either 1, 2, or 3 in compliance with the last census (<https://www.dane.gov.co/index.php/servicios-al-ciudadano/servicios-informacion/estratificacion-socioeconomica>). Apart from these factors, education and home structure were also reported by participants. Figure 1 shows the statistical distribution of participants' age according to these variables.

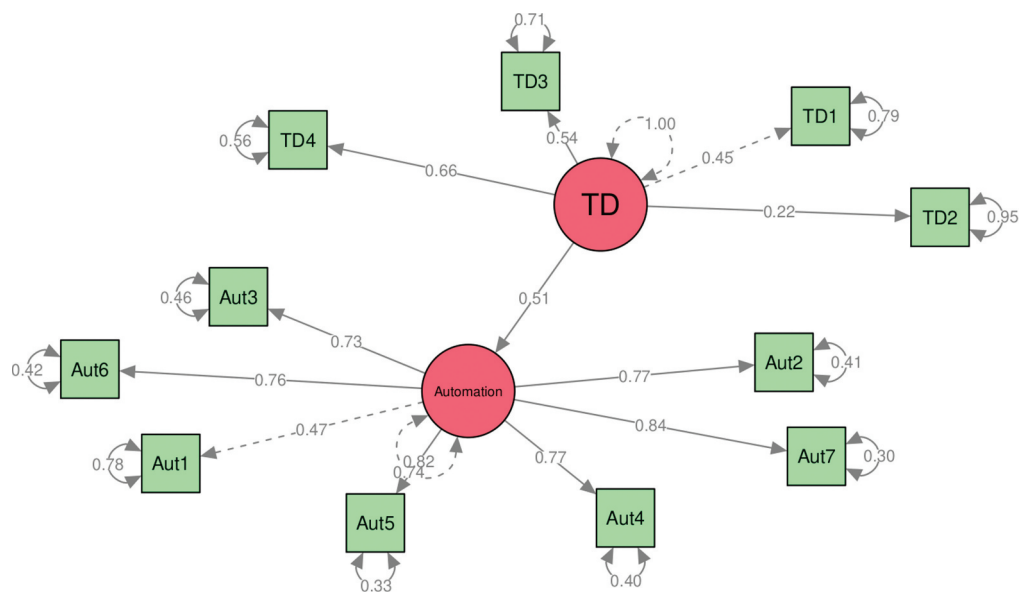
The data curation as well as the data analyses were documented in adherence with the standards of reproducible research (Epskamp, 2019) following criteria of open-science (Gandrud, 2013), with a special emphasis on open-science in psychology (Shrout & Rodgers, 2018). Interested readers in reproducing the results of this study are welcome to visit the supplemental material in the following repository <https://github.com/jcorrean/Fin-Tech>. The appendix at the end of this manuscript provides additional guidance for those interested in replicating the results.

4. Results

We proceeded by analysing the measurement properties of our two principal constructs: technology disposition and use of automated financial products. For both of these constructs, we conducted an exploratory analysis on their items variance—co variance matrix. The exploratory analysis consisted of evaluating the sampling adequacy of their scale items through the Kaiser-Meyer-Olkin test (Dziuban & Shirkey, 1974), as well as testing the assumptions of tau-equivalence and homogeneous items following standards of robust psychometric analysis (Zhang & Yuan, 2016). Testing these assumptions are useful to decide whether the factor structure of the scales is uni-dimensional or not, which in turn is relevant for structural model specification purposes (Bollen, 2002).

The overall sampling adequacy for automation revealed that the items of the automation scale are susceptible to factorisation (KMO = 0.92). Nonetheless, a parallel analysis suggests that the

Figure 2. Structural model of technology disposition and use of automated banking services in low-income Colombian consumers.



possible number of factors equals two, while the number of components equals one. Here, the conceptual distinction between factors and components is of paramount importance. According to Kim (2008), common factor analysis only focuses on the reliable common variance of data, while principal component analysis focuses on all the variance of data.

In order to determine the underlying psychometric structure, we followed the guidelines of the approach proposed by Zhang and Yuan (2016) who distinguished between the so-called tau-equivalence test and the homogeneous items test. The tau-equivalence test evaluates whether a one-factor model with equal factor loadings adequately fits the data, while the homogeneous items test evaluates whether a one-factor model with freely estimated factor loadings adequately fits the data. The results from the tau-equivalence test ($F = 1.563$; $p < 0.0575$) revealed that a one factor model with equal factor loadings for all items is not a valid solution, although the idea of a one-factor model with freely estimated factor loadings seems to be a valid assumption ($F = 1.763$; $p = 0.0415$), and the results of a confirmatory factor analysis revealed an acceptable goodness-of-fit ($CFI = .950$; $TLI = 0.926$; $RMSEA = 0.142$; $SRMR = 0.037$). The resulting reliability estimates of this scale also revealed acceptable levels (Cronbach's $\alpha = 0.94$; McDonald's $\Omega = 0.94$).

Likewise, the Kaiser-Meyer-Olkin test revealed that the four items of technology disposition are susceptible of factorisation ($KMO = 0.67$) with one factor as captured by the tau-equivalence test ($F = 7.37$; $p = 0.000$). This result proved to be coherent with those of a confirmatory factor analysis with an acceptable goodness-of-fit ($CFI = 0.996$; $TLI = 0.987$; $RMSEA = 0.034$; $SRMR = 0.018$) and reliability estimates (Cronbach $\alpha = 0.57$; McDonald's $\Omega = 0.59$). Figure 2 shows both measurement models and their relationship. The descriptive statistics of each item and their reliability estimates and standard deviation are summarised in Table 1.

Our structural model, estimated with the lavaan package in R (Oberski et al., 2014), revealed a statistical and significant relationship ($\beta = 0.513$; $p < 0.001$) between the technology disposition (as an antecedent of) use of automated banking services in low-income Colombian consumers ($CFI = 0.941$; $TLI = 0.924$; $RMSEA = 0.094$; $SRMR = 0.042$).

Table 1. Statistical descriptives and reliability estimates of individual items

Dimension	Item	Mean (St. Deviation)	Cronbach's α (SE)
Technology	TD1. The Internet makes my life easier	7.71	0.43
Disposition	by saving me time and effort	(2.40)	(0.04)
	TD2. I can use a new application or service	6.82	0.69
	by myself on the Internet	(3.17)	(0.02)
	TD3. The Internet is the best means of staying	7.26	0.51
Automation	in contact with people and businesses	(2.48)	(0.04)
	TD4. It is important for me to use the Internet	8.13	0.45
	to stay connected in order to use different	(2.22)	(0.04)
	applications and services.		
	AUT 1. Allow financial analyses from a	4.98	0.924
	specialised robot	(3.16)	(0.005)
	AUT2. Allow a consultation service from	5.07	0.930
a specialised robot	(3.21)	(0.004)	
AUT 3. Allow a specialised robot to handle	4.34	0.933	
questions, claims, or complaints	(3.13)	(0.004)	
AUT 4. Invest in a financial product	4.23	0.929	
recommended by a specialised robot	(2.99)	(0.004)	
AUT 5. Allow a specialised robot to analyze	5.10	0.925	
income and expenses	(3.28)	(0.005)	
AUT 6. Allow all banking transactions to be	4.10	0.930	
mediated by a specialised robot	(2.93)	(0.004)	
AUT 7. Allow the management of product	4.76	0.925	
or services through a specialised robot	(3.11)	(0.05)	

The standardised parameter estimates along with their p-values and confidence intervals are summarised in Table 2.

Several findings are worth noting from the above results. First, our estimated model (see, Figure 2) revealed that 26.3% of the variance of the disposition to use automation banking products and services proved to be accounted for technology disposition in low-income Colombian consumers. Secondly, the magnitude of all standard parameter estimates are high, with low standard errors, and their relationships proved to be statistically significant. To summarise, the results revealed that low-income consumers in

Table 2. Standardised parameter estimates of the structural model

Parameter	Estimate	SE	p-value	CI (Lower-Upper)
Automation → Aut1	0.473	0.018	0	0.438–0.508
Automation → Aut2	0.768	0.021	0	0.727–0.810
Automation → Aut3	0.733	0.024	0	0.687–0.779
Automation → Aut4	0.772	0.021	0	0.731–0.813
Automation → Aut5	0.818	0.018	0	0.783–0.853
Automation → Aut6	0.763	0.022	0	0.721–0.806
Automation → Aut7	0.838	0.017	0	0.805–0.870
Tech Disp → TD1	0.453	0.013	0	0.428–0.479
Tech Disp → TD2	0.216	0.055	0	0.107–0.324
Tech Disp → TD3	0.541	0.049	0	0.445–0.637
Tech Disp → TD4	0.661	0.049	0	0.565–0.757
Tech Disp → Automation	0.513	0.050	0	0.415–0.610

Colombia show favourable disposition to accept and use automated banking and financial services.

5. Discussion

Financial inclusion, roughly understood as the availability and equality of opportunities to access financial services, is one of the most important challenges for banking and financial institutions. Automation of these services, in turn, represents a second great challenge as a promising mechanism that broadens coverage through scaling economies targeting developing countries (Nazaritehrani & Mashali, 2020). Consequently, this paper aimed to evaluate the effect of technology disposition over use of automated financial services in low-income Colombian banking consumers. The selection of these variables relied on their relevance for consumers and their ease of use for managers to employ it in strategic planning processes. The results confirmed the contribution of technology disposition to explain the use of automated banking services. Several contributions are worth mentioning in this regard.

Common wisdom points out a series of stereotypes regarding low-income consumers' educational profile and general living conditions, such as being resistant to or lacking the skills to adopt new technologies. The results presented in this work are relatively distant from these stereotypes. Indeed, our findings are consistent with previous successful cases of novel banking services developed in emerging economies. They concur with the idea that technology itself is not a barrier to consumers of this market (Akhter et al., 2020). At least three factors have contributed to increased opportunities in this current situation. First, thanks to the popularised use of mobiles, low-income consumers are likely to reduce the limitations of educational background and lack of resources (e.g., with an Internet connection, they have access to banking services and the benefits they provide). Second, the mobility restrictions due to Covid-19 and the fear of using cash have forced the population to use contactless services and automated systems to attend to their needs (Anderson et al., 2020). Third, implementing technology to fulfil basic activities reinforces technological literacy (e.g., essential scheduling services, billing services such as top-up public transport, and other prepaid services).

In summary, these new habits represent a disruptive change in consumption and consumer behaviour that benefit the disposition to use technology and reduce the barriers to use automated banking services (Sheth, 2020). In this new normal, the evolution of consumer behaviour and technology empowerment has changed at a faster rate than technological advances in financial services to meet the needs of consumers at the bottom of the pyramid. Aligned with these results, the items related to cellular connection and the ability to accomplish tasks alone show the higher

contribution on this factor (TD3—TD4). Likewise, the automation items most valued by customers were associated with managing existing products and requesting new banking services.

5.1. Theoretical and practical implications

The current study revealed that consumers' disposition alone was useful to explain a significant part of the use of automated financial services. This insight is particularly meaningful. More sophisticated approaches including additional theoretical factors or dimensions were not necessary. This implies the possibility of developing more parsimonious models in further endeavours. Developing a simpler model provides straightforward and applicable strategies for managers, as they avoid dealing with complex conceptualisations that make it difficult for organisations to benefit from the results. In addition to the traditional approaches based on collecting variables via self-reports (such as those based on TAM or UTAUT), we regard the inclusion of new methodologies as external validity criterion resources. Thanks to the increasing use of powerful tools aiming to evaluate customer transactions, it might be pertinent to develop non-verbal measurement procedures based on customers' behaviour, respecting the information confidentiality (Davis, 1989; Prahalad & Prahalad, 2005; Sunderaraman et al., 2020; Venkatesh et al., 2012). This last form of behavioural measurement would represent an important evolution in the theoretical approach to the study of technology use. For example, customers use of multiple channels and the way these channels are employed (e.g., contactless payment methods, mobile payments, transfers) can be considered as behavioural proxies of technology disposition. Business data analytic techniques in this way become a fundamental tool for banking and financial firms, as they help to retrieve and analyse these metrics as a means of non-invasive data collection. This posits another practical implication. Leaders in the banking sector should be willing to join forces with applied computer scientists and information engineers to harness these disciplines' pragmatic advances. In this regard, the present study represents a significant contribution since the measurement scale, although developed considering the existing literature, was adapted from the vision of professionals responsible for developing automated services in the banking sector. Likewise, the fieldwork in alliance with Brandstrat allowed for national coverage and representativeness of the findings, since traditionally, academic research in this field, except when it is carried out with secondary data, rarely has comprehensive geographical coverage.

Developing and encouraging research-and-development teams collaborating with marketing and other departments will become the best practices of banking firms committed to digital business transformation (Beccalli et al., 2020). From this data driven perspective, another implication is the way banks and financial institutions conceptualise and implement their segmentation of customers. For example, instead of segmentation based upon traditional variables, it might be based upon what is revealed real-time by what a customer does on a website or a smartphone app (Stone et al., 2020). The potential impacts that these best practices might have on financial inclusion are not even considered in previous efforts, but we foresee that they will be scrutinised in further research.

Currently, sustainability, inclusion, and entrepreneurship are vital axes for developing organisations, and a large part of business schools globally are committed to these aspects to generate social impact. The academic research in business schools is not exempt from the commitment to serve and transform people and organisations, especially the most vulnerable groups (Ortiz-de Urbina-criado et al., 2022).

Low-income are classified as the young, the poor, who lack confidence in achieving their financial goals, and fraud victims. These vulnerable groups call for significant attention from policymakers and educators to improve their financial capability and improve their financial well-being (Xiao & Porto, 2021). As the majority of the low-income consumers are cautious buyers; product price, utility, and awareness become significant factors in influencing their purchase behaviour and well-being (Roy et al., 2021).

6. Limitations and implications for further research

The current study is not free of limitations. As compared with more recent references in the literature, this work proposed a uni-dimensional evaluation of consumers' disposition to use automated banking services. However, this assessment is admittedly limited as compared with other models proposing

evaluations aimed at different customers' disposition stages. For example, the work of Baabdullah et al. (2019) highlights a dimensional evaluation of the disposition to adopt information systems. This evaluation should rely on the dimensions of information quality, system quality and service quality, as suggested by T. Zhou (2013) in the case of mobile payment systems. A critical reader might suggest that our evaluation is lagging behind more recent efforts. We regard that this evaluation is a first step that pave the way for further efforts harnessing more sophisticated models. One of these models might be the study of Shareef et al. (2018) who describe three phases in the disposition to accept mobile banking: static (information search), interaction (interacting with providers through two-way communication) and transaction (associating the bank account with applications and performing operations), each with distinctive determining factors.

Numerous studies have shown that the interaction with financial applications is different depending on their characteristics, their complexity and the financial risk they imply. The use of an application to make payments cannot be equated with its application to bank transfers, the purchase of insurance and the management of savings.

In addition, previous studies have evaluated social factors and their use to predict technology disposition. Malaquias and Hwang (2019) showed that in developed countries social influence is important to predict the use of technology, while in emerging economies ease of use is key to predict the habit of using applications, highlighting the importance of usability also in the early stages of interaction with technology. For this reason we suggest comparing the effect of risk with social and functional factors in order to conclude their influence on low-income customers.

As technology adoption is influenced by context and digital literacy, the current study is limited to the Colombian context. In order to contribute to the generalisation of these results, it is appropriate to reply to this research in multiple contexts. Aligned with this suggestion, previous studies have demonstrated that this sector should re-targeted to create a more customised services (Dakduk et al., 2020; Prahalad & Prahalad, 2005). Customising services in this context imply, among other things, recognising the differences that emerge among customers. For example, some customers are more prone to request ready-to-use savings mechanisms, while others prefer credits.

These previous recommendations could be simultaneously implemented in further research in order to confirm to cultural effects and the difference across low-income customers in emerging economies. Given that the life conditions of the bottom of pyramid customers in emerging countries could vary in terms of the technological infrastructure and public policies to promote technological development. Staying at home has accelerated the relationship between consumers and suppliers, creating profound shifts in digital behaviour (Knowles et al., 2020). However, a traditional barrier in making electronic transactions is a lack of financial services for low-income consumers. Aiding the evolution in digital maturity largely depends on the development of value propositions that promote financial inclusion.

Funding

This work was supported by the Colegio de Estudios Superiores de Administración under grant number [11019].

Author details

Juan C. Correa¹
E-mail: juan.correan@cesa.edu.co
ORCID ID: <http://orcid.org/0000-0002-0301-5641>
Silvana Dakduk²
E-mail: sm.dakduk@uniandes.edu.co
ORCID ID: <http://orcid.org/0000-0003-4700-5354>
David van der Woude²
E-mail: davidv@cesa.edu.co
ORCID ID: <http://orcid.org/0000-0003-1682-9481>
Marithza Sandoval-Escobar³
E-mail: marithza.sandoval@konradlorenz.edu.co
ORCID ID: <http://orcid.org/0000-0003-1938-0675>
Rafael Lopez-Llamas²

E-mail: rafael@brandstrat.co

ORCID ID: <http://orcid.org/0000-0002-5819-8270>

¹ CESA Business School, Colegio de Estudios Superiores de Administración -CESA, Casa Echavarría - Diagonal 34 # 5A-23 Tercer Piso, Bogotá, Colombia.

² Universidad de Los Andes, Bogotá, Colombia.

³ Fundación Universitaria Konrad Lorenz, Bogotá, Colombia.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Supplementary material

Supplemental data for this article can be accessed online at <https://doi.org/10.1080/23311975.2022.2071099>

Citation information

Cite this article as: Low-income consumers' disposition to use automated banking services, Juan C. Correa, Silvana

Dakduk, David van der Woude, Marithza Sandoval-Escobar & Rafael Lopez-Llamas, *Cogent Business & Management* (2022), 9: 2071099.

References

- E. I. U. (2019). Global microscope 2019: The enabling environment for financial inclusion. <https://www.cen-terforfinancialinclusion.org/global-microscope-2019>
- Agidi, R. C. (2018). Biometrics: The future of banking and financial service industry in Nigeria. *International Journal of Electronics and Information Engineering*, 9(2), 91–105. doi:10.6636/IJEIE.201812.9(2).04
- Akhter, A., Al Asheq, A., Hossain, M. U., & Karim, M. M. (2020). Exploring customers' intention to adopt mobile banking services: Evidence from a developing country. *Banks and Bank Systems*, 15(2), 105–116. [https://doi.org/10.21511/bbs.15\(2\).2020.10](https://doi.org/10.21511/bbs.15(2).2020.10)
- Albashrawi, M., & Yu, J. (2020). Usage behavior of m-banking: An analytical perspective. In *Proceedings of the 24th Pacific Asia Conference on Information Systems: Information Systems (IS) for the Future*. Dubai 20th to 24th June 2020: Association for Information Systems.
- Alemu, T., Bandyopadhyay, T., & Negash, S. (2015). Electronic payment adoption in the banking sector of low-income countries. *International Journal of Information Systems in the Service Sector (IJISSS)*, 7(4), 27–47. <https://doi.org/10.4018/IJISSS.2015100102>
- Ali, A. & Subramanian, R. (2022). Current status of research on mobile banking: An analysis of literature. *Vision*. <https://doi.org/10.1177/09722629211073268>
- Anderson, C., Bieck, C., & Marshall, A. (2020). How business is adapting to covid-19: Executive insights reveal post-pandemic opportunities. *Strategy & Leadership*, 49(1), 38–47. doi:10.1108/SL-11-2020-0140
- Andrianaivo, M., & Kpodar, K. (2012). Mobile phones, financial inclusion, and growth. *Review of Economics and Institutions*, 3(2), 30. <https://doi.org/10.5202/rei.v3i2.75>
- Arun, T., & Kamath, R. (2015). Financial inclusion: Policies and practices. *IIMB Management Review*, 27(4), 267–287. <https://doi.org/10.1016/j.iimb.2015.09.004>
- Auletta, N., González, R., & Armas, V. (2019). 1Star+ Banca Comunitaria Banesco: La banca va al barrio. *Scala: Distribución Inclusiva*. Business Association of Latin American Studies. <https://observatorioscala.undes.edu.co/images/2018/PDF/casos/Banca-Comunitaria-Banesco.pdf>
- Baabdullah, A., Alalwan, A., Rana, N., Kizgin, H., & Patil, P. (2019). Consumer use of mobile banking (m-banking) in Saudi Arabia: Towards an integrated model. *International Journal of Information Management*, 44, 38–52. <https://doi.org/10.1016/j.ijinfomgt.2018.09.002>
- Beccalli, E., Elliot, V., & Virili, F. (2020). Artificial intelligence and ethics in portfolio management. In A. Agrifoglio, R. Lamboglia, D. Mancini, & F. Ricciardi (Eds.), *Digital business transformation: organizing, managing and controlling in the information age* (pp. 19–30). Springer.
- Benbasat, I., & Barki, H. (2007). Quo vadis TAM? *Journal of the Association for Information Systems*, 8(4), 211–218. <https://doi.org/10.17705/1jais.00126>
- Bollen, K. A. (2002). Latent variables in psychology and the social sciences. *Annual Review of Psychology*, 53(1), 605–634. <https://doi.org/10.1146/annurev.psych.53.100901.135239>
- Camarero, C. (2007). Relationship orientation or service quality? *International Journal of Bank Marketing*, 25(6), 406–426. <https://doi.org/10.1108/02652320710820354>
- Chauhan, S., Akhtar, A., & Gupta, A. (2022). Customer experience in digital banking: A review and future research directions. *International Journal of Quality and Service Sciences*, 14(2), 311–348. <https://doi.org/10.1108/IJQSS-02-2021-0027>
- Coppack, M., Raza, Y., Sarker, S., & Scribbons, K. (2015). Consumer vulnerability. *Occasional Paper*, 8, 71–72. <https://web.actuaries.ie/sites/default/files/erm-resources/occasional-paper-8.pdf>
- D'Andrea, G., & Stengel, E. (2004). 6 truths about emerging-market consumers. *Strategy+Business*, (34), 58–69. <https://www.strategy-business.com/article/04106>
- da Costa Nogami, V. K., & Veloso, A. R. (2017). Disruptive innovation in low-income contexts: Challenges and state-of-the-art national research in marketing. *RAI Revista de Administração e Inovação*, 14(2), 162–167. <https://doi.org/10.1016/j.rai.2017.03.005>
- Dakduk, S., Santalla-Banderalli, Z., & Siqueira, J. R. (2020). Acceptance of mobile commerce in low-income consumers: Evidence from an emerging economy. *Heliyon*, 6(11), e05451. <https://doi.org/10.1016/j.heliyon.2020.e05451>
- Davis, F. D. (1986). *Technology acceptance model for empirically testing new end-user information systems theory and results* [Massachusetts Institute of Technology: Ph.D. thesis].
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Dziuban, C. D., & Shirkey, E. C. (1974). When is a correlation matrix appropriate for factor analysis? some decision rules. *Psychological Bulletin*, 81(6), 358. <https://doi.org/10.1037/h0036316>
- Epskamp, S. (2019). Reproducibility and replicability in a fast-paced methodological world. *Advances in Methods and Practices in Psychological Science*, 2(2), 145–155. <https://doi.org/10.1177/2515245919847421>
- Fernández-Olit, B., Martín, J. M. M., & González, E. P. (2019). Systematized literature review on financial inclusion and exclusion in developed countries. *International Journal of Bank Marketing*, 38(3), 600–626. <https://doi.org/10.1108/IJBM-06-2019-0203>
- Financiera, S. (2020). Estrategia Nacional de Inclusión Financiera. (Report 10084716)
- Foster, M. N., & Rhoden, S. L. (2020). The integration of automation and artificial intelligence into the logistics sector. *Worldwide Hospitality and Tourism Themes*, 12(1), 56–68. <https://doi.org/10.1108/WHATT-10-2019-0070>
- Gandrud, C. (2013). *Reproducible research with R and R studio*. CRC Press.
- Grigoli, F., Koczan, Z., & Topalova, P. (2020). Automation and labor force participation in advanced economies: Macro and micro evidence. *European Economic Review*, 126, 103443. <https://doi.org/10.1016/j.euroecorev.2020.103443>
- Hamilton, K. L., & Catterall, M. (2005). Towards a better understanding of the low income consumer. *Advanc Es in Consumer Research*, 32(1), 627–632. <https://strathprints.strath.ac.uk/4533/>
- Hart, S. L., & Christensen, C. M. (2002). The great leap: Driving innovation from the base of the pyramid. *MIT Sloan Management Review*, 44(1), 51. Retrieved from <https://www.proquest.com/scholarly-journals/great-leap-driving-innovation-base-pyramid/docview/224960526/se-2?accountid=17203>

- Huterska, A., Piotrowska, A. I., & Szalacha-Jarmużek, J. (2021). Fear of the covid-19 pandemic and social distancing as factors determining the change in consumer payment behavior at retail and service outlets. *Energies*, 14(14), 4191. <https://doi.org/10.3390/en14144191>
- Jonker, N., van der Crujisen, C., Bijlsma, M., & Bolt, W. (2020, December). *Pandemic payment patterns* (Working Paper No. 701). Amsterdam: DeNederlandscheBank.
- Kamran, S., & Uusitalo, O. (2019). Banks' unfairness and the vulnerability of low-income unbanked consumers. *The Service Industries Journal*, 39(1), 65–85. <https://doi.org/10.1080/02642069.2018.1436704>
- Kaplinsky, R., Chataway, J., Clark, N., Hanlin, R., Kale, D., Muraguri, L., Papaioannou, T., Robbins, P., & Wamae, W. (2009). Below the radar: What does innovation in emerging economies have to offer other low-income economies? *International Journal of Technology Management & Sustainable Development*, 8(3), 177–197. <https://doi.org/10.1386/ijtm.8.3.177/1>
- Karjaluoto, H., Shaikh, A. A., Saarijärvi, H., & Saraniemi, S. (2019). How perceived value drives the use of mobile financial services apps. *International Journal of Information Management*, 47, 252–261. <https://doi.org/10.1016/j.ijinfomgt.2018.08.014>
- Kim, H.-J. (2008). Common factor analysis versus principal component analysis: Choice for symptom cluster research. *Asian Nursing Research*, 2(1), 17–24. [https://doi.org/10.1016/S1976-1317\(08\)60025-0](https://doi.org/10.1016/S1976-1317(08)60025-0)
- Knowles, J., Ettenson, R., Lynch, P., & Dollens, J. (2020). Growth opportunities for brands during the covid-19 crisis. *MIT Sloan Management Review*, 61(4), 2–6. Retrieved from <https://www.proquest.com/scholarly-journals/growth-opportunities-brands-during-covid-19/docview/2406643113/se-2?accountid=17203>
- Liao, C., Huang, Y.-J., & Hsieh, T.-H. (2016). Factors influencing internet banking adoption. *Social Behavior and Personality: An International Journal*, 44(9), 1443–1455. <https://doi.org/10.2224/sbp.2016.44.9.1443>
- Malaquias, R., & Hwang, Y. (2019). Mobile banking use: A comparative study with Brazilian and U.S. participants. *International Journal of Information Management*, 44, 132–140. <https://doi.org/10.1016/j.ijinfomgt.2018.10.004>
- Mejía-Escobar, J. C., González-Ruiz, J. D., & Duque-Grisales, E. (2020). Sustainable financial products in the latin america banking industry: Current status and insights. *Sustainability*, 12(14), 5648. <https://doi.org/10.3390/su12145648>
- Met, İ., Kabukçu, D., Uzunoğulları, G., Soyalp, Ü., & Dakdevir, T. (2020). Transformation of business model in finance sector with artificial intelligence and robotic process automation. In U. Hacıoglu (Eds.), *Digital business strategies in blockchain ecosystems*. Contributions to Management Science. (pp. 3–29). Springer, Cham. https://doi.org/10.1007/978-3-030-29739-8_1
- Meyer, C., Cohen, D., & Nair, S. (2020). From automats to algorithms: The automation of services using artificial intelligence. *Journal of Service Management*, 31(2), 145–161. <https://doi.org/10.1108/JOSM-05-2019-0161>
- Mhlanga, D. (2021). Financial inclusion in emerging economies: The application of machine learning and artificial intelligence in credit risk assessment. *International Journal of Financial Studies*, 9(3), 3. <https://doi.org/10.3390/ijfs9030039>
- Mogaji, E., Adeola, O., Hinson, R., Nguyen, N., Nwoba, A., & Soetan, T. (2021). Marketing bank services to financially vulnerable customers: Evidence from an emerging economy. *International Journal of Bank Marketing*, 39(3), 402–428. <https://doi.org/10.1108/IJBM-07-2020-0379>
- Mohan, L., & Potnis, D. (2017). Real-time decision-making to serve the unbanked poor in the developing world. In *Proceedings of the 2017 acm sigmis conference on computers and people research* (pp. 183–184). Bangalore India: Association for Computing MachineryNew YorkNYUnited States.
- Morgan-Thomas, A., & Veloutsou, C. (2013). Beyond technology acceptance: Brand relationships and online brand experience. *Journal of Business Research*, 66(1), 21–27. <https://doi.org/10.1016/j.jbusres.2011.07.019>
- Morgan, P. J., & Long, T. Q. (2020). Financial literacy, financial inclusion, and savings behavior in Laos. *Journal of Asian Economics*, 68, 101197. <https://doi.org/10.1016/j.asieco.2020.101197>
- Mushtaq, R., & Bruneau, C. (2019). Microfinance, financial inclusion and ICT: Implications for poverty and inequality. *Technology in Society*, 59, 101154. <https://doi.org/10.1016/j.techsoc.2019.101154>
- Myeni, S., Makate, M., & Mahonye, N. (2020). Does mobile money promote financial inclusion in Eswatini? *International Journal of Social Economics*, 47(6), 693–709. <https://doi.org/10.1108/IJSE-05-2019-0310>
- Nazaritehrani, A., & Mashali, B. (2020). Development of e-banking channels and market share in developing countries. *Financial Innovation*, 6(12), 1–19. <https://doi.org/10.1186/s40854-020-0171-z>
- Oberski, D. et al. (2014). lavaan. survey: An R package for complex survey analysis of structural equation models. *Journal of Statistical Software*, 57(1), 1–27. <https://doi.org/10.18637/jss.v057.i01>
- Ortiz-de Urbina-criado, M., Mora-Valentín, E.-M., & Nájera-Sánchez, -J.-J. (2022). Sustainability and entrepreneurship: Emerging opportunities for business and management education. *Journal of Entrepreneurship in Emerging Economies*. <https://doi.org/10.1108/JEEE-12-2021-0471>
- Pandey, D., Mukherjee, S., Das, G., & Zhang, J. (2022). Improving base-of-the-pyramid consumer welfare through mobile technology services. *Journal of Services Marketing*, 36(2), 232–244. <https://doi.org/10.1108/JSM-05-2021-0179>
- Pelletier, A., Khavul, S., & Estrin, S. (2019). Innovations in emerging markets: The case of mobile money. *Industrial and Corporate Change*, 29 (2), 395–421. doi:10.1093/icc/dtz049
- Prahalad, C. K., & Prahalad, C. K. (2005). *The fortune at the bottom of the pyramid*. Wharton School Pub.
- R Core Team. (2022). *R: A language and environment for statistical computing [Computer software manual]*. <https://www.R-project.org/>
- Ramírez-Correa, P., Grandón, E. E., & Rondán-Cataluña, F. J. (2020). Users segmentation based on the technological readiness adoption index in emerging countries: The case of Chile. *Technological Forecasting and Social Change*, 155, 120035. <https://doi.org/10.1016/j.techfore.2020.120035>
- Rastogi, S., & Ragabiruntha, E. (2018). Financial inclusion and socioeconomic development: Gaps and solution. *International Journal of Social Economics*, 45(7), 1122–1140. <https://doi.org/10.1108/IJSE-08-2017-0324>
- Ratten, V., & Ratten, H. (2007). Social cognitive theory in technological innovations. *European Journal of*

- Innovation Management*, 10(1), 90–108. <https://doi.org/10.1108/14601060710720564>
- Roy, G., Debnath, R., Mitra, P. S., & Shrivastava, A. K. (2021). Analytical study of low-income consumers' purchase behaviour for developing marketing strategy. *International Journal of System Assurance Engineering and Management*, 12(5), 895–909. doi:10.1007/s13198-021-01143-6
- Shareef, M. A., Baabdullah, A., Dutta, S., Kumar, V., & Dwivedi, Y. K. (2018). Consumer adoption of mobile banking services: An empirical examination of factors according to adoption stages. *Journal of Retailing and Consumer Services*, 43, 54–67. <https://doi.org/10.1016/j.jretconser.2018.03.003>
- Sheth, J. (2020). Impact of covid-19 on consumer behavior: Will the old habits return or die? *Journal of Business Research*, 117, 280–283. <https://doi.org/10.1016/j.jbusres.2020.05.059>
- Shrout, P. E., & Rodgers, J. L. (2018). Psychology, science, and knowledge construction: Broadening perspectives from the replication crisis. *Annual Review of Psychology*, 69(1), 487–510. <https://doi.org/10.1146/annurev-psych-122216-011845>
- Sithole, N., Sullivan Mort, G., & D'Souza, C. (2021). Building blocks of financial inclusion through customer experience value at financial touchpoints in Southern Africa. *International Journal of Bank Marketing*, 39(3), 360–380. <https://doi.org/10.1108/IJBM-07-2020-0409>
- Soudien, N., Ladhari, R., & Chaouali, W. (2021). Mobile banking adoption: A systematic review. *International Journal of Bank Marketing*, 39(2), 214–241. <https://doi.org/10.1108/IJBM-04-2020-0182>
- Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., Laughlin, P., Machtynger, J., & Machtynger, L. (2020). Artificial intelligence (AI) in strategic marketing decision-making: A research agenda. *The Bottom Line*, 33(2), 183–200. <https://doi.org/10.1108/BL-03-2020-0022>
- Sunderaraman, P., Ho, S., Chapman, S., Joyce, J., Colvin, L., Omollo, S., Pleshkevich, M., & Cosentino, S. (2020). Technology use in everyday financial activities: Evidence from online and offline survey data. *Archives of Clinical Neuropsychology*, 35(4), 385–400. <https://doi.org/10.1093/arclin/acz042>
- Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2021). Consumer acceptance and use of information technology: A meta-analytic evaluation of utaut2. *Information Systems Frontiers*, 23(4), 987–1005. <https://doi.org/10.1007/s10796-020-10007-6>
- Tarafdar, M., Anekal, P., & Singh, R. (2012). Market development at the bottom of the pyramid: Examining the role of information and communication technologies. *Information Technology for Development*, 18(4), 311–331. <https://doi.org/10.1080/02681102.2012.690172>
- Teo, A., Tan, G., Ooi, K., Hew, T., & Yew, K. (2015). The effects of convenience and speed in m-payment. *Industrial Management and Data Systems*, 115(2), 311–331. <https://doi.org/10.1108/IMDS-08-2014-0231>
- Thoene, U., & Turriago-Hoyos, A. (2017). Financial inclusion in Colombia: A scoping literature review. *Intangible Capital*, 13(3), 582–614. <https://doi.org/10.3926/ic.946>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. doi:10.2307/41410412
- Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, 17(5), 328–376. <https://doi.org/10.17705/1jais.00428>
- Verkijika, S. F. (2020). An affective response model for understanding the acceptance of mobile payment systems. *Electronic Commerce Research and Applications*, 39, 100905. <https://doi.org/10.1016/j.elerap.2019.100905>
- Wenner, G., Bram, J. T., Marino, M., Obeysekare, E., & Mehta, K. (2018). Organizational models of mobile payment systems in low-resource environments. *Information Technology for Development*, 24(4), 681–705. <https://doi.org/10.1080/02681102.2017.1311830>
- Xiao, J., & Porto, N. (2021). Financial capability and well-being of vulnerable consumers. *Journal of Consumer Affairs*, 1–15. <https://doi.org/10.1111/joca.12418>
- Yurdakul, D., Atik, D., & Dholakia, N. (2017). Redefining the bottom of the pyramid from a marketing perspective. *Marketing Theory*, 17(3), 289–303. <https://doi.org/10.1177/1470593117704265>
- Zhang, Z., & Yuan, K.-H. (2016). Robust coefficients alpha and omega and confidence intervals with outlying observations and missing data: Methods and software. *Educational and Psychological Measurement*, 76(3), 387–411. <https://doi.org/10.1177/0013164415594658>
- Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. *Decision Support Systems*, 54(2), 1085–1091. <https://doi.org/10.1016/j.dss.2012.10.034>
- Zhou, Y., & Tyers, R. (2019). Automation and inequality in China. *China Economic Review*, 58, 101202. <https://doi.org/10.1016/j.chieco.2018.07.008>

Appendix

The data preprocessing was conducted in R (R Core Team, 2022), and it required to open the raw data frame, and select the columns of the items for the technology disposition scale, and the items for the disposition to use automation banking services, as follows,

```
library(readr)

Brandstat <- read_delim("RawDataBrandstat.csv",
",", escape_double = FALSE, trim_ws = TRUE)

automation <- Brandstat[14:20]

TD <- Brandstat[10:13]

library(psych)

describe.by(Brandstat$Age, group = Brandstat$Sex, mat = TRUE, digits = 2)
```

The statistical analyses of the present study was organised into three interrelated parts. The first and second part deal with the psychometric properties of the measurement models of automation and technology disposition, respectively. The third part deals with the parameter estimation of structural relationships between the two measurement models previously estimated.

7.1. Automation Measurement Model

The initial step of the analysis required the evaluation of items sampling adequacy with the Kaiser-Meyer-Olkin test, as implemented by the R package "psych" and the Tau-equivalence test and Homogeneous items test, as implemented by the R package "coefficientalpha". The codes for these test were as follows,

```
library(psych)

KMO(automation)

library(coefficientalpha)

tau.test(automation)
```

The specification for the measurement model of automation was conducted in R, with the aid of lavaan package (Oberski et al., 2014), and other related packages. The programming syntax in R is exactly as follows,

```
library(lavaan)

aut.model <- "aut =~ Aut1 + Aut2 + Aut3 + Aut4 + Aut5 + Aut6 + Aut7"

fit1 <- lavaan::cfa(aut.model, data=Brandstat,std.lv=TRUE)

summary(fit1, fit.measures=T,standardized=T)
```

After estimating the parameters of the model, further reliability estimates and visualization outcomes were done as follows,

```
library(semPlot)

reliability(fit1)

semPaths(fit1, whatLabels = "stand", layout = "tree", color = list(

lat = rgb(255, 100, 118, maxColorValue = 255),

man = rgb(155, 253, 175, maxColorValue = 255)),

mar = c(10, 5, 10, 5), intercepts = FALSE, residuals = FALSE, nCharNodes = 0)
```

The previous syntaxes return the results of items sampling adequacy, robust reliability estimates, a short table with the parameter estimates for the automation measurement model, the reliability estimates for the entire scale, and a visualization of the measurement model (not included here, but available in the supplemental material, in the following repository address: <https://github.com/jcorrean/Fin-Tech/blob/master/ModelExplorationAndTesting.pdf>).

7.2. Technology Disposition Measurement Model

In a similar vein, the statistical analysis for the technology disposition measurement model were as follows,

```
library(psych)

KMO(TD)

library(coefficients)

tau.test(TD)

library(lavaan)

td.model <- "TD =~ TD1 + TD2 + TD3 + TD4"

fit2 <- lavaan::cfa(td.model, data=Brandstat,std.lv=TRUE)

summary(fit2, fit.measures=T,standardized=T)

library(semTools)

reliability(fit2)

library(semPlot)

semPaths(fit2, whatLabels = "stand", layout = "tree", color = list(

lat = rgb(255, 100, 118, maxColorValue = 255),

man = rgb(155, 253, 175, maxColorValue = 255)),
```

```
mar = c(10, 5, 10, 5), intercepts = FALSE, residuals = FALSE, nCharNodes = 0)
```

7.3. A Structural Model of Technology Disposition and Automation

In this part of the analysis, we set previous measurement models as parts of a structural equation model that defines the disposition to use automation banking services as the principal endogenous latent variable (Bollen, 2002), and technology disposition as the main exogenous variable. The specification of this model was as follows,

```
library(lavaan);  
  
modelData <- Brandstat  
  
model<-"  
  
! regressions  
  
Automation=~Aut__Aut1*Aut1  
  
Automation=~Aut__Aut2*Aut2  
  
Automation=~Aut__Aut3*Aut3  
  
Automation=~Aut__Aut4*Aut4  
  
Automation=~Aut__Aut5*Aut5  
  
Automation=~Aut__Aut6*Aut6  
  
Automation=~Aut__Aut7*Aut7  
  
TD=~TD__TD1*TD1  
  
TD=~TD__TD4*TD4  
  
TD=~TD__TD2*TD2  
  
TD=~TD__TD3*TD3  
  
TD=~TD__Automation*Automation  
  
! residuals, variances and covariances  
  
Automation ~ 1.0*Automation  
  
Aut1 ~ VAR_Aut1*Aut1  
  
Aut2 ~ VAR_Aut2*Aut2  
  
Aut3 ~ VAR_Aut3*Aut3  
  
Aut4 ~ VAR_Aut4*Aut4
```

```
Aut5 ~ VAR_Aut5*Aut5
Aut6 ~ VAR_Aut6*Aut6
Aut7 ~ VAR_Aut7*Aut7
TD ~ 1.0*TD
TD1 ~ VAR_TD1*TD1
TD4 ~ VAR_TD4*TD4
TD2 ~ VAR_TD2*TD2
TD3 ~ VAR_TD3*TD3
! observed means
Aut1~1;
Aut2~1;
Aut3~1;
Aut4~1;
Aut5~1;
Aut6~1;
Aut7~1;
TD1~1;
TD4~1;
TD2~1;
TD3~1;
";
result<- sem(model, data=modelData);
summary(result, fit.measures=TRUE);
standardizedSolution(result)
inspect(result, "rsquare")
library(semPlot)
semPaths(result, whatLabels = "std", layout = "spring", color = list(
```

```
lat = rgb(255, 100, 118, maxColorValue = 255),
```

```
man = rgb(155, 253, 175, maxColorValue = 255)),
```

```
mar = c(10, 5, 10, 5), intercepts = FALSE, residuals = FALSE, nCharNodes = 0)
```



© 2022 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.

You are free to:

Share — copy and redistribute the material in any medium or format.

Adapt — remix, transform, and build upon the material for any purpose, even commercially.

The licensor cannot revoke these freedoms as long as you follow the license terms.

Under the following terms:

Attribution — You must give appropriate credit, provide a link to the license, and indicate if changes were made.

You may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use.

No additional restrictions

You may not apply legal terms or technological measures that legally restrict others from doing anything the license permits.



***Cogent Business & Management* (ISSN: 2331-1975) is published by Cogent OA, part of Taylor & Francis Group.**

Publishing with Cogent OA ensures:

- Immediate, universal access to your article on publication
- High visibility and discoverability via the Cogent OA website as well as Taylor & Francis Online
- Download and citation statistics for your article
- Rapid online publication
- Input from, and dialog with, expert editors and editorial boards
- Retention of full copyright of your article
- Guaranteed legacy preservation of your article
- Discounts and waivers for authors in developing regions

Submit your manuscript to a Cogent OA journal at www.CogentOA.com

