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Determinants of digital financial inclusion in Latin America and the Caribbean

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Abstract

Purpose – This study investigates the determinants of digital financial inclusion (DFI) in Latin America and the Caribbean (LAC), focusing on the influence of sociodemographic factors on the accessibility and use of digital financial services. The analysis is based on the World Bank's Global Financial Inclusion Database from 2021.
Design/methodology/approach – An index variable was created by grouping all questions related to the accessibility and use of digital financial services into a single measure, which draws on information from the Global Findex Survey covering 15 countries from LAC. In addition, a probit model was employed to assess the demographic determinants of DFI.
Findings – The findings indicate that sociodemographic factors such as age, education, gender, income, employment status and country of origin significantly influence DFI.
Research limitations/implications – The study primarily examines sociodemographic factors, potentially overlooking other crucial determinants, including infrastructure, regulatory frameworks and cultural influences that are likely to play significant roles.
Practical implications – Policymakers should develop inclusive policies to address barriers such as digital literacy and internet access while enhancing fintech innovation and infrastructure in countries with lower adoption rates, thereby promoting broader financial inclusion across the region.
Social implications – The findings offer valuable insights for policymakers and service providers in LAC to enhance DFI, especially among marginalized population groups, namely women or people with lower income and education levels.
Originality/value – This study contributes original insights into the understanding of DFI in LAC by highlighting the influence of sociodemographic factors within the context of a rapidly evolving digital landscape.

Keywords Financial inclusion, Digital financial inclusion, Financial services, Access to financial markets, Digital payments, Latin America
Paper type Research article

1. Introduction

Digital financial inclusion (DFI) refers to the access to and use of financial services through digital platforms, such as mobile phones, the internet and fintech solutions, to expand the reach

JEL Classification — E23, E44, E69, G18, O11, O16, O57

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of traditional financial services and reduce access barriers, especially for marginalized populations (Ozili, 2018). In recent years, digital financial inclusion (DFI) has been recognized as a key instrument for improving financial inclusion, enabling millions of people without access to traditional banking to make payments, obtain credit and participate in the digital economy. However, despite their transformative potential, the adoption of these services varies significantly across the regions. This study aims to identify the sociodemographic determinants that influence the access and use of digital financial services in Latin America and the Caribbean (LAC).

According to the World Bank's Global Findex Database (2021), financial inclusion has substantially advanced over the past decade. Globally, account ownership has reached 76% of the adult population, up from 62% in 2014 (Demirgüç-Kunt *et al.*, 2022). In developing economies, 71% of adults now have an account with a financial institution or mobile money provider, an increase of 30 percentage points over the last ten years. Financial inclusion has also improved considerably in LAC. Excluding high-income economies, 73% of adults now have access to an account, marking an increase of 18.5 percentage points since 2017 (Demirgüç-Kunt *et al.*, 2022). This rise represents the most substantial improvement among developing regions, positioning account ownership in LAC slightly above the average for developing economies (Findev Gateway, 2022). However, despite these advances, millions of people around the world remain unbanked. The most commonly reported barriers among unbanked adults include insufficient financial resources, long distances to financial institutions and the lack of necessary documentation (Demirgüç-Kunt *et al.*, 2022).

Access to a mobile phone is essential for people to open a bank account and engage in financial services. The digitalization of the financial sector has transformed how millions of people access money, enabling transactions and services without the need to visit a physical branch. Nevertheless, in LAC, the adoption of digital financial services remains uneven. Although its potential is enormous, factors such as education, infrastructure and regulations limit its expansion, excluding the most vulnerable sectors that could greatly benefit from these solutions. For instance, Issahaku *et al*. (2023) find that well-targeted policy interventions can help overcome these barriers by reducing access costs and fostering broader adoption of DFI.

This study explores the sociodemographic determinants of DFI in LAC using data from the Global Findex Database. It seeks to answer the following question: What sociodemographic factors shape access to and use of digital technologies and financial services in the region? To address this, a DFI index was developed using principal component analysis (PCA). The index integrates various metrics of access to and use of digital financial services, and econometric models (probit) are subsequently employed to evaluate the associations between factors such as gender, age, educational level, income, employment status, and country of residence and levels of DFI.

The main results indicate that sociodemographic factors are significant in assessing DFI. The study identified positive correlations between DFI and factors such as young adulthood, male gender, employment status, higher educational attainment, higher income levels and residence in countries with high fintech adoption rates. These findings highlight the specific population that should be the focus of public and private policies aimed at improving DFI: those with the lowest levels of income and education, women, the unemployed and those living in Latin American countries lagging in fintech adoption. Finally, to complement the analysis and enhance its robustness, the probit model was applied separately to each digital service included in the survey. The results closely aligned with those obtained by regressing the index on the sociodemographic factors considered.

Understanding the determinants of DFI is particularly important, as numerous studies have shown that the financial inclusion gap in developing countries remains substantial (Carballo, 2017; Rojas-Suárez, 2016; Demirgüç-Kunt *et al.*, 2015). However, empirical research on specific drivers and barriers to DFI in LAC is still scarce. This study seeks to address this gap by providing evidence on the population groups most affected by exclusion and offering policy recommendations aimed at fostering broader and more equitable DFI in the region.

The study is organized as follows: Section 2 provides a theoretical framework; Section 3 reviews the literature on financial inclusion at both the global and regional levels, with a focus on Latin America; Section 4 describes the research methodology; Section 5 presents the results and offers recommendations for policymakers; and Section 6 concludes.

2. Theoretical framework

This study is framed within the digital agent theory of financial inclusion, which explains how providers of digital financial services interact with users to facilitate adoption and use of these services (Ozili, 2024). This theory maintains that financial inclusion does not depend solely on the availability of digital services but on the ability of digital agents to reduce access barriers, improve financial education and generate trust in the digital system. Through this perspective, the present study analyzes how sociodemographic factors influence the adoption of digital financial services in LAC, identifying the challenges and opportunities to strengthen financial inclusion in the region.

Demirgüç-Kunt *et al.* (2015) define financial inclusion as access to affordable and valuable financial services that help individuals and businesses satisfy their needs. These services include storing, sending and receiving money safely, preparing for emergencies and making productive investments in areas such as health and education. When individuals lack access to formal financial services, they depend on informal mechanisms, for example, cash, which can be riskier and more expensive, according to Rojas-Suárez (2016). Given this, financial inclusion plays a crucial role in welfare and poverty reduction, as highlighted by policymakers and academics (Demirgüç-Kunt *et al.*, 2015).

Technological advancements have expanded financial inclusion, leading to DFI, where financial transactions are cashless and technology-driven (Banna and Alam, 2020).

The increasing importance of technology has shifted the focus from traditional financial inclusion to digital DFI. Scholars, particularly Shepherd (2004) and Tsatsou (2020), argue that technological innovation drives social and economic transformations, improving the quality of life and social inclusion. This shift has introduced concepts, namely fintech, a term combining finance and technology, which describes how modern internet-based technologies (e.g. cloud computing, mobile internet) integrate with traditional financial services, for example, money lending and transaction banking.

DFI seeks to integrate unbanked people into the formal financial system, offering essential financial services through digital devices including mobile phones, computers and other technologies (Ozili, 2018, 2020). This process involves providing accessible financial services to excluded groups and communities, using tools, for example, electronic money accounts, mobile payments, debit and credit cards, online banking and point-of-sale terminals (Xie and Chen, 2024). The fundamental elements comprise digital devices to access the services, sales agents that facilitate transactions, additional financial products such as credit and insurance, digital platforms for providing services and servers. The providers of these services are full- and limited-service banks, mobile network operators and non-bank electronic money issuers, all operating within a digital infrastructure that connects users to financial services.

Studies on technology adoption, particularly about digital financial services, have identified several factors influencing this process. For instance, Davis (1989) used the Technology Acceptance Model to demonstrate that the main factors affecting technology adoption are the user's perceived usefulness and access. Later studies, specifically Venkatesh *et al.* (2003) and Ananda *et al.* (2020), have emphasized additional factors, primarily security, privacy, trust, social influence and available resources, as key drivers of adoption. Therefore, to foster the successful adoption of digital financial services, providers must carefully assess the underlying factors that influence uptake and design targeted strategies that address barriers to access, especially among population groups facing greater challenges in using these technologies (Anane and Nie, 2022). Evidence from various contexts highlights the transformative potential of digital finance. For instance, it has helped reduce physical barriers to financial services, primarily for marginalized groups such as women and rural populations (Aziz and Naima, 2021). In India, the expansion of digital payment tools has led to notable improvements in the speed, efficiency, accuracy and overall effectiveness of public service delivery (Nandru *et al.*, 2021). Similarly, in Uganda, policy measures, in particular tax exemptions on mobile money transactions, have contributed to economic growth by incentivizing the use of digital financial innovations (Bongomin *et al.*, 2020).

The importance of digital financial services gained significant prominence during the COVID-19 pandemic, when technology played an important role in facilitating the adoption and development of digital financial services to support contactless policies to combat the spread of the virus. This was more evident in the use of banking applications to store and transfer money, in some cases with the help of traditional providers and, in other cases, with the help of *fintech* companies (Demirgüç-Kunt *et al.*, 2022). Thus, given the distinction between the concepts of financial inclusion and DFI, the findings in the literature on the determinants of financial inclusion should be separated from those related to DFI.

3. Literature review

Regarding financial inclusion, studies made by Ozili (2020), Motta and Gonzalez Farias (2022), Martinez *et al.* (2020), and Balliester Reis (2022) found that sociodemographic factors have a direct impact on financial inclusion. The main determinants identified by these authors are gender, income level, education, age, employment and country of residence.

Based on their findings, the results show a positive relationship between higher income education levels and financial inclusion. Regarding gender, Motta and Gonzalez Farias (2022) and Balliester Reis (2022) reported no evidence supporting the existence of a gender gap. In contrast, in their study conducted in Latin America, Martinez *et al.* (2020) discovered a positive relationship between being a woman and higher levels of financial inclusion. Employment status is another factor closely related to income level, which positively connects with financial inclusion.

Age is a less straightforward relationship factor, as it is influenced by various elements such as a person's income level and country of residence. Age sometimes correlates with lower financial inclusion, particularly in low-income countries. However, the relationship is different in higher-income countries, with higher inclusion up to a certain age and a subsequent decline, as shown by Balliester Reis (2022). Other authors, for example Martinez *et al.* (2020), observed that age also matters. Older people are more likely to use formal accounts, savings and credit than younger people. Borg and Smith (2018) and Ali (2023) reported that age negatively relates to technology adoption for financial services. Younger people use these services more as a result of earlier technological adoption and easy access from devices with fewer requirements than traditional financial products.

Other studies, including those by Liu *et al.* (2021), Xi and Wang (2023), Borg and Smith (2018), Ali (2023), and Demir *et al.* (2022), have also identified that various sociodemographic factors such as gender, income level, education, age, employment status and country of residence significantly affect DFI.

Ali (2023) has recently identified a negative relationship between DFI and being male. A more comprehensive analysis of this sociodemographic variable can be found in Gammage *et al.* (2017), which indicates that women experience reduced access to DFI compared with men and are less inclined to utilize digital financial services despite their availability. Income level, educational attainment and employment significantly affect DFI. Individuals with higher incomes, educational levels and employment levels are more likely to use digital financial products. According to Xi and Wang (2023), this is mainly because people in urban areas have greater access to the financial system and technological infrastructure. In addition, urban dwellers typically have higher income and educational levels than their rural counterparts, thus strengthening the association between income and DFI. This is primarily the result of the increased ability to obtain quality connectivity and formal financial education in urban areas.

Finally, some authors have found that the country of residence can be critical for DFI. Antonijevi *et al.* (2021) examined the relationship between a country's income level, GDP per capita and the adoption of digital payment services. Their research reveals a significant positive correlation between a country's income level and the use of digital payment services: as national income rises, citizens are increasingly inclined to use digital financial services for payments. Demir *et al.* (2022) investigated the effect of fintech adoption, government regulation and telecommunications infrastructure on DFI. They found that the adoption of fintech technologies in a country is positively correlated with participation in digital financial services. Other relevant subfactors include mobile phone penetration, technological infrastructure, adoption rates, stable and secure network access, and state regulations and laws.

To date, DFI has not received considerable attention in the literature specifically focused on Latin America. However, a few studies (Orazi *et al.*, 2023; Khera *et al.*, 2022; Clavijo *et al.*, 2019; Rousset *et al.*, 2021) provide valuable insights on this topic. First, women have weaker ties to financial inclusion than men. Second, these studies highlight a growing trend among young people toward using digital financial services, which was not previously evident in the broader financial inclusion context. Third, financial literacy and access to financial products highly correlate with education level; indeed, previous research shows that individuals with higher education tend to possess better financial literacy and have more options for financial products available to them. Finally, in terms of income, Orazi *et al.* (2023) found that people in middle-income segments are more inclined to use digital banking than those in either high- or low-income segments.

To conclude, it is important to mention another article by Nandru *et al.* (2021) that significantly impacted the objectives and methodology of this study. The authors researched factors that affect access to and use of digital financial services in India by examining extensive data on demographic characteristics such as gender, age, income, education and employment status. They reported that education and income are crucial determinants of DFI.

Although these studies provide academic insight into the topic, there is a lack of research on the determinants of DFI specific to Latin America. To address this gap, the present study aims to investigate the influence of these determinants in LAC by working with the Global Findex Database. One distinctive aspect of this research is the creation of an index involving the assignment of weights based on the degree of significance of each variable to assess the relationship between sociodemographic factors and the extent of DFI.

4. Method

4.1 Data

This study draws on the 2021 edition of the Global Findex Database, which is based on nationally representative surveys of approximately 128,000 adults across 123 countries. The primary aim of the survey was to assess how individuals engage with financial services—such as payments, savings and borrowing—and how they manage key financial events, including major expenses or income shocks. This survey has been conducted in four waves: 2011, 2014, 2017 and 2021. The most recent wave includes updated indicators on access to and use of both formal and informal financial services, including cards, mobile phones and the internet, to make and receive digital payments. The main objective was to study the determinants of DFI in LAC; variables related to accessibility and use of digital financial services were considered in the investigation. These variables are derived from survey questions that respondents were asked about their ownership or use of specific digital financial services. Furthermore, to complement the statistical analysis of the main variables, a correlation matrix of all accessibility and use variables of digital financial services is provided in Table 10 (see Appendix). From its results, it can be highlighted that all the variables are positively correlated, the lowest correlation being 0.1636 (between *Has a mobile account* and *Has a debit card*) and the highest 0.8001 (between *Has made a digital merchant payment* and *Has used a debit card*). This fact supports a statement that was expected *a priori:* the accessibility or use of a financial service increases the probability that an individual has access to or uses another financial service.

In addition to considering the variables related to the accessibility and use of digital financial services, the model includes sociodemographic variables as explanatory factors: gender, education, income, age, country and employment (see Table 3).

The Global Findex Database (2021) covers 15 countries, which were divided into three groups depending on the level of influence of the fintech sector in each economy (see Table 1). The number of active fintech companies was used in each country to measure the influence of the fintech sector. The categorization of fintech penetration levels (high, medium, low) was determined using the distribution of the number of active fintech firms across countries. Countries positioned above the 75th percentile were classified as high penetration, those between the 25th and 75th percentiles as medium penetration, and those below the 25th percentile as low penetration. This information was obtained from Finnovating's report: Fintech Global Vision 2023. In the present study, Table 2 shows the descriptive statistics for the sociodemographic variables and the variables related to the accessibility and use of financial services.

Regarding access, it can be seen that the percentage of men with debit cards is slightly higher than that of women, 21.50% compared to 20.21%. However, it is noteworthy that a significant proportion of women, 36.59%, do not have access to a debit card, which is higher than the proportion of men without this access. Similarly, it is observed that the difference in credit card ownership is more pronounced, with 31.56% of women lacking access compared to 18.08% of men. The access gap to mobile accounts is also notable, where 46.55% of women do not have access, compared to 31.51% of men.

With respect to digital financial services, evidence suggests that gender disparity persists. For example, only 13.02% of men and 11.80% of women make online payments. Furthermore, when the use of mobile phones for bill payments is examined, 12.55% of men and 10.56% of women use this option, while more than 40% of both genders do not use this technology. These statistics highlight persistent disparities in access to and use of digital financial services between men and women, which invite reflection on the barriers women still face in this area. The following sections of this paper will examine the causes of these gaps and explore potential solutions to promote greater financial inclusion.

4.2 Probit regressions

Based on the work developed by Nandru *et al.* (2021), a probit model was used. An individual model was estimated for each dependent variable related to accessibility and use of digital financial services, yielding a total of 13 different probit models. Considering that demographic

Table 1. Categorization of countries by the influence of the fintech sector on their economies

High influence of the fintech sector (Group 1)	Medium influence of the fintech sector (Group 2)	Low influence of the fintech sector (Group 3)
Argentina	Bolivia	El Salvador
Brazil	Costa Rica	Honduras
Colombia	The Dominican Republic	Jamaica
Ecuador	Panama	Nicaragua
Peru	Paraguay	Venezuela

Note(s): Data recovered from Finnovating's report: Fintech Global Vision (2023). The classification of countries is based on the influence of the fintech sector on each economy, measured by the number of active fintech companies

Source(s): Authors' elaboration

Table 2. Descriptive statistics on access to and use of digital financial services by gender

	Variables	Men (yes)	Women (yes)	Men (no)	Women (no)
Access	Has a debit card	21.50%	20.21%	21.70%	36.59%
	Has a credit card	18.08%	14.54%	31.56%	32.82%
	Has a mobile account	11.63%	10.31%	31.51%	46.55%
Use	Has used a debit card	11.63%	10.22%	31.01%	46.59%
	Has used a credit card	9.08%	5.91%	40.56%	44.45%
	Has used a mobile phone or the internet to access the account	26.87%	23.21%	22.77%	27.15%
	Has used a mobile phone or the internet to check an account balance	28.97%	25.11%	20.67%	25.25%
	Has made bill payments online using the internet	13.02%	11.80%	30.16%	45.02%
	Has paid a utility bill using a mobile phone	12.55%	10.56%	32.00%	44.89%
	Has made or received a digital payment	13.40%	17.98%	28.36%	40.25%
	Has made a digital merchant payment	15.83%	13.80%	27.36%	43.02%

Source(s): Authors' elaboration using the Global Findex Database (2021)

variables are the explanatory variables of the study, for the dependent variable $(j = 1, \ldots, 13)$, the probability for individual i is given by:

$$P_1\left[y_{i,j} = 1 | x_i\right] = \Phi(\beta_0 + \beta_1 Gender_i + \beta_2 Age_i + \beta_3 Employment_i) \tag{1}$$

$$P_2 = \Phi(\beta_0 + \beta_1 Gender_i + \beta_2 Age_i + \beta_3 Employment_i + \beta_4 Education_i) \tag{2}$$

$$P_3 = \Phi(\beta_0 + \beta_1 Gender_i + \beta_2 Age_i + \beta_3 Employment_i + \beta_4 Education_i + \beta_5 Income_i) \tag{3}$$

$$P_4 = \Phi(\beta_0 + \beta_1 Gender_i + \beta_2 Age_i + \beta_3 Employment_i + \beta_4 Education_i + \beta_5 Income_i + \beta_6 Country_i) \tag{4}$$

where $\Phi(\cdot)$ is the cumulative normal standard distribution.

4.3 Principal component analysis

Instead of considering each of the 13 questions about accessibility and use of digital financial services separately and estimating 13 different models, a better approach could consist of considering an index variable that groups all the questions into one single measure. This approach allows for estimating only one model that simultaneously accounts for all possible sources of DFI. To achieve this, the PCA is used. The PCA is a statistical method to reduce the dimensionality of a dataset by linearly transforming the data into a new coordinate system, where most of the variation in the data can be explained with fewer dimensions than the initial data (Jolliffe, 2013). In this study, the proposed index variable is developed using the first principal component, which integrates information from the 13 variables of interest. This strategy is in line with Cardona-Montoya *et al.* (2022), who also apply PCA to summarize multiple survey indicators into composite indexes for their empirical analysis.

This index is denoted as I. Once the index is defined, the following regression models are applied to explore the determinants of DFI.

$$I_1 = \Phi(\gamma_0 + \gamma_1 Gender_i + \gamma_2 Age_i + \gamma_3 Employment_i) \tag{5}$$

$$I_2 = \Phi(\gamma_0 + \gamma_1 Gender_i + \gamma_2 Age_i + \gamma_3 Employment_i + \gamma_4 Education_i) \tag{6}$$

Table 3. Descriptive statistics of sociodemographic variables

	Freq.	%
Economy		
Argentina	1,003	6.9
Bolivia	1,000	6.9
Brazil	1,002	6.9
Colombia	1,000	6.9
Costa Rica	1,001	6.9
The Dominican Republic	1,000	6.9
Ecuador	1,000	6.9
El Salvador	1,002	6.9
Honduras	1,000	6.9
Jamaica	502	3.5
Nicaragua	1,007	6.9
Panama	1,002	6.9
Paraguay	1,000	6.9
Peru	1,000	6.9
Venezuela, RB	1,000	6.9
Country category		
Group 3 Low influence of the fintech sector	4,511	31.07
Group 2 Medium influence of the fintech sector	5,003	34.46
Group 1 High influence of the fintech sector	5,005	34.47
Life cycle		
Under 18 years of age	473	3.3
18–25	2,864	19.8
26–35	3,253	22.4
36–49	3,543	24.4
50–64	2,793	19.3
More than 65	1,573	10.8
Education level		
Completed primary school or less	3,890	27.1
Completed secondary school	7,788	54.3
Completed secondary education or more	2,665	18.6
Housing income		
Quin1	2,347	16.17
Quin2	244	16.81
Quin3	2,641	18.19
Quin4	3,215	22.14
Quin5	3,876	26.70
Is the respondent in the workforce?		
No	3,548	24.44
Yes	10,971	75.56

Source(s): Authors’ elaboration using the Global Findex Database (2021)

$$I_3 = \Phi(\gamma_0 + \gamma_1 Gender_i + \gamma_2 Age_i + \gamma_3 Employment_i + \gamma_4 Education_i + \gamma_5 Income_i) \tag{7}$$

$$I_4 = \Phi(\gamma_0 + \gamma_1 Gender_i + \gamma_2 Age_i + \gamma_3 Employment_i + \gamma_4 Education_i + \gamma_5 Income_i + \gamma_6 Country_i) \tag{8}$$

5. Results

To analyze the determinants of DFI, probit models are estimated using three dependent variables that reflect different dimensions of financial inclusion. These include access to digital financial services (*Has a mobile account*), use of these services (*Has used a mobile account*) and participation in digital transactions (*Has made or received digital payment*). Selecting these variables allows for a comprehensive assessment of DFI, as they represent key aspects of access, use and integration in the digital economy.

The variable *Has a mobile account* indicates whether an individual has a mobile financial account, whether from a traditional bank or a digital provider. *Has used a mobile account* to measure the active use of these accounts, reflecting effective DFI. Finally, *Has made or received a digital payment* evaluates participation in electronic payment systems, which is essential to reduce the use of cash and improve economic connectivity (see Table 3).

Table 4 presents the results. The findings reveal a negative relationship between life cycle and account ownership, indicating that younger individuals have greater access to digital financial services. Notably, individuals over 65 years show higher DFI than individuals aged 50–64. All life-cycle variables are statistically significant, except for the 18–25 age group, which becomes relevant only when country effects are included. Women exhibit lower DFI than men, while employment positively correlates with mobile account ownership. Higher education and income levels also increase the likelihood of accessing digital financial services, particularly for those with tertiary education or in the highest income quintile. Additionally, individuals in countries with higher fintech penetration have greater DFI.

Subsequently, the relationship between mobile account use and the determinants of DFI is analyzed. Table 5 reports that younger individuals, women and those outside the workforce are less likely to use mobile accounts. In contrast, higher education and income levels considerably increase mobile account adoption. Country-specific factors such as fintech market penetration also influence use, with lower penetration correlating with decreased adoption. The model's explanatory power improves as more variables are added, reinforcing the importance of these factors in understanding mobile account use.

Table 6 presents the relationship between digital payments and sociodemographic factors, showing a consistent trend with previous models (Tables 5 and 6) for gender, employment, education, income and country category.

A key difference emerges in age dynamics. Individuals aged 18–25 are significantly more likely to make digital payments than those under 18, marking a shift from earlier models. For the 26–35 age group, the initial model showed no statistical relevance, but after including education and income levels, a positive correlation appeared. In the final model, the 26–35, 36–49 and 50–64 age groups did not reveal statistically important relationships with digital payments.

As a robustness check, likelihood ratio tests were conducted for all probit models to compare nested models for each dependent variable. Table 7 presents the results, confirming that the models become more explanatory as more variables are included. Additionally, an Localization Receiver Operating Characteristic (LROC) test was performed, showing areas under the ROC curve of 0.7217, 0.7415 and 0.7408, respectively. These values suggest that the models possess a fair to good discriminatory capacity, effectively differentiating between positive and negative cases and outperforming random chance.

While useful for analyzing individual aspects of financial inclusion, the previous results are limited, as they assess only one dimension at a time. To address this, a DFI index was developed using PCA analysis (as detailed in the methodology) to provide a comprehensive measure. The index incorporates thirteen variables, including both digital and traditional financial inclusion indicators, ensuring greater robustness. Table 8 presents the selected variables, and their weights are based on the first principal component.

Table 9 shows a statistically significant relationship between the DFI index and sociodemographic factors. Age has a negative relationship with the index, indicating that younger individuals have greater access to digital financial services. Women exhibit lower

Table 4. Probit estimations

Variables	Has a mobile account (1)	Has a mobile account (2)	Has a mobile account (3)	Has a mobile account (4)
LifeCycle: 18–25 years old	−0.0318	−0.0462	−0.0421	−0.0729*
	(0.0389)	(0.0398)	(0.0400)	(0.0404)
LifeCycle: 26–35 years old	−0.154***	−0.115***	−0.114***	−0.166***
	(0.0387)	(0.0401)	(0.0403)	(0.0408)
LifeCycle: 36–49 years old	−0.397***	−0.298***	−0.327***	−0.391***
	(0.0428)	(0.0448)	(0.0451)	(0.0458)
LifeCycle: 50–64 years old	−0.752***	−0.599***	−0.638***	−0.713***
	(0.0620)	(0.0651)	(0.0655)	(0.0663)
LifeCycle: Over 65 years old	−0.352***	−0.287***	−0.261***	−0.295***
	(0.0844)	(0.0853)	(0.0856)	(0.0860)
Female	−0.253***	−0.243***	−0.211***	−0.186***
	(0.0275)	(0.0280)	(0.0283)	(0.0285)
Are they in the workforce?	0.376***	0.298***	0.282***	0.270***
	(0.0374)	(0.0384)	(0.0385)	(0.0389)
Secondary school completed		0.478***	0.421***	0.314***
		(0.0374)	(0.0380)	(0.0391)
Tertiary education or more completed		0.804***	0.667***	0.572***
		(0.0436)	(0.0458)	(0.0467)
Income level: Quin2			0.0765	0.0817
			(0.0527)	(0.0531)
Income level: Quin3			0.126**	0.138***
			(0.0510)	(0.0514)
Income level: Quin4			0.276***	0.281***
			(0.0486)	(0.0490)
Income level: Quin5			0.386***	0.407***
			(0.0480)	(0.0485)
Country category: 2				0.187***
				(0.0364)
Country category: 1				0.441***
				(0.0331)
Constant	−0.750***	−1.162***	−1.313***	−1.429***
	(0.0468)	(0.0567)	(0.0652)	(0.0677)
LR χ^2	588.11	928.55	1022.40	1203.33
Pseudo *R*	0.0486	0.0775	0.0853	0.1004
Observations	11,501	11,348	11,348	11,348

Note(s): Standard errors are in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Column (1) presents the results of a probit model analyzing the availability of a mobile account in relation to life cycle, gender and employment. Columns (2), (3) and (4) show the same probit model with additional control variables: education, income level and country category, added in that sequence. The country category groups countries based on fintech market penetration into three categories
Source(s): Authors' elaboration

levels of DFI than men, while employment status has a positive effect, suggesting that labor force participation enhances financial inclusion.

On the other hand, higher education and income levels positively correlate with the DFI index, with individuals in the highest income quintile and higher education levels accessing more digital financial services. Countries with greater fintech penetration also show higher inclusion, though Category 3 (low fintech penetration) countries unexpectedly exhibit higher financial inclusion than Category 2 (medium penetration) countries. Finally, Table 9 indicates that the R-squared increases as more determinants are added in models (2), (3) and (4), improving the model's predictive power.

Table 5. Probit estimations between *Has used a mobile account* and determinants

Variables	Has used a mobile account (1)	Has used a mobile account (2)	Has used a mobile account (3)	Has used a mobile account (4)
LifeCycle: 18–25 years old	−0.189***	−0.260***	−0.259***	−0.258***
	(0.0449)	(0.0463)	(0.0467)	(0.0469)
LifeCycle: 26–35 years old	−0.383***	−0.394***	−0.393***	−0.398***
	(0.0442)	(0.0459)	(0.0463)	(0.0465)
LifeCycle: 36–49 years old	−0.527***	−0.520***	−0.572***	−0.586***
	(0.0482)	(0.0506)	(0.0512)	(0.0515)
LifeCycle: 50–64 years old	−0.939***	−0.909***	−0.983***	−0.998***
	(0.0638)	(0.0685)	(0.0693)	(0.0698)
LifeCycle: Over 65 years old	−0.241*	−0.156	−0.150	−0.193
	(0.140)	(0.142)	(0.143)	(0.143)
Female	−0.181***	−0.196***	−0.150***	−0.144***
	(0.0300)	(0.0310)	(0.0315)	(0.0316)
Are they in the workforce?	0.360***	0.312***	0.304***	0.283***
	(0.0437)	(0.0453)	(0.0456)	(0.0458)
Secondary school completed		0.714***	0.625***	0.603***
		(0.0506)	(0.0513)	(0.0518)
Tertiary education or more completed		1.280***	1.089***	1.095***
		(0.0539)	(0.0560)	(0.0564)
Income level: Quin2			0.109*	0.104
			(0.0656)	(0.0659)
Income level: Quin3			0.160**	0.162**
			(0.0626)	(0.0629)
Income level: Quin4			0.409***	0.402***
			(0.0588)	(0.0591)
Income level: Quin5			0.579***	0.566***
			(0.0576)	(0.0579)
Country category: 2				−0.284***
				(0.0414)
Country category: 1				0.0669*
				(0.0391)
Constant	0.129**	−0.589***	−0.832***	−0.731***
	(0.0549)	(0.0731)	(0.0847)	(0.0881)
LR χ^2	510.83	1158.14	1329.08	1428.23
Pseudo *R*	0.0491	0.1122	0.1287	0.1383
Observations	7,509	7,449	7,449	7,449

Note(s): Standard errors are in parentheses $***p < 0.01$, $**p < 0.05$, $*p < 0.1$
Column (1) presents the results of a probit model analyzing the use of a mobile account and life cycle, gender and employment. Columns (2), (3) and (4) show the same probit model with additional control variables: education, income level, and country category, added in that sequence. The country category groups countries based on fintech market penetration into three categories
Source(s): Authors' elaboration

The study results reinforce the idea that DFI is a key factor in improving access to and use of appropriate financial services. As proposed by the digital agent theory of financial inclusion (Anane and Nie, 2022), the digitalization of financial services depends on the interaction between digital service providers and users, who face structural and personal barriers in adopting digital services. In this sense, the findings confirm that age, gender, education, income, employment status and fintech market penetration significantly influence the access to and use of mobile financial services.

The results corroborate a gender gap in DFI, consistent with Ali (2023). The negative and relevant relationship between being female and access to digital services indicates that women

Table 6. Probit estimation between digital payments and determinants

Variables	Has made a digital payment (1)	Has made a digital payment (2)	Has made a digital payment (3)	Has made a digital payment (4)
LifeCycle: 18–25 years old	0.115***	0.106***	0.113***	0.0978***
	(0.0328)	(0.0340)	(0.0342)	(0.0344)
LifeCycle: 26–35 years old	0.0111	0.0829**	0.0836**	0.0533
	(0.0320)	(0.0336)	(0.0338)	(0.0341)
LifeCycle: 36–49 years old	−0.116***	0.0326	−0.00217	−0.0377
	(0.0338)	(0.0360)	(0.0363)	(0.0366)
LifeCycle: 50–64 years old	−0.151***	0.0736*	0.0280	−0.00752
	(0.0411)	(0.0444)	(0.0448)	(0.0451)
LifeCycle: Over 65 years old	−0.646***	−0.554***	−0.528***	−0.555***
	(0.0675)	(0.0686)	(0.0688)	(0.0692)
Is female	−0.238***	−0.233***	−0.193***	−0.172***
	(0.0220)	(0.0229)	(0.0232)	(0.0234)
Are they in the workforce?	0.447***	0.367***	0.353***	0.341***
	(0.0268)	(0.0278)	(0.0280)	(0.0282)
Secondary school completed		0.612***	0.544***	0.455***
		(0.0273)	(0.0277)	(0.0285)
Tertiary education or more completed		1.300***	1.135***	1.068***
		(0.0362)	(0.0379)	(0.0384)
Income level: Quin2			0.135***	0.135***
			(0.0382)	(0.0383)
Income level: Quin3			0.181***	0.191***
			(0.0375)	(0.0377)
Income level: Quin4			0.330***	0.336***
			(0.0365)	(0.0367)
Income level: Quin5			0.512***	0.541***
			(0.0367)	(0.0371)
Country Category: 2				0.145***
				(0.0277)
Country Category: 1				0.435***
				(0.0285)
Constant	−0.0654*	−0.630***	−0.828***	−0.955***
	(0.0361)	(0.0436)	(0.0492)	(0.0516)
LR χ^2	823.73	2216.59	2450.42	2697.26
Pseudo R	0.0412	0.1123	0.1241	0.1366
Observations	14,499	14,324	14,324	14,324

Note(s): Standard errors are in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Column (1) shows the results of a probit model where the variable *Has made a digital payment* is related to life cycle, gender, and employment, while columns (2), (3) and (4) present the same probit model with other control variables, namely education, income level and country category. The country category groups countries based on fintech market penetration in each nation
Source(s): Authors' elaboration

face more considerable barriers, highlighting the need for strategies to reduce these inequalities and encourage more equitable adoption.

According to the digital agent theory, these findings suggest that financial providers should apply differentiated strategies to encourage the adoption of digital services among women and low-income people. This involves improving access to technology and strengthening digital financial education to achieve more inclusive and sustainable adoption. In conclusion, the research results reinforce the idea that DFI depends on the availability of services and the

Table 7. LRT test

Model	Dependent variables	Has a mobile account LR	*p*-value	Has used a mobile account LR	*p*-value	Has made a digital payment LR	*p*-value
A	Life Cycle + Gender + Workforce	–	–	–	–	–	–
B	Life Cycle + Gender + Workforce + Educ Level	459.55***	0	730.57***	0	1648.75***	0
C	Life Cycle + Gender + Workforce + Educ Level + Income Level	93.84***	0	170.93***	0	233.83***	0
D	Life Cycle + Gender + Workforce + Educ Level + Income Level + Country Category	180.93***	0	99.15***	0	246.84***	0

Note(s): *** *p*-value rejecting the null hypothesis. The null hypothesis states that the base model is better than the model with more variables, according to LRT. Comparisons are as follows: Model A (base) vs. Model B; Model B (base) vs. Model C; and Model C (base) vs. Model D, for each of the independent variables

Source(s): Authors' elaboration

Table 8. Index and weight data

Variable	Type	Weight	Accum.
Has a debit card	Access	46.810%	46.810%
Has a credit card	Access	11.390%	58.200%
Has a mobile account	Access	9.620%	67.820%
Has used a debit card	Use	6.520%	74.340%
Has used a credit card	Use	5.520%	79.860%
Has used a mobile account	Use	5.190%	85.050%
Has used a mobile account to check account balance	Use	4.460%	89.510%
Has made payments online	Use	3.340%	92.850%
Has paid a utility bill online	Use	3.000%	95.850%
Has made a digital payment	Use	2.510%	98.360%
Has made a digital merchant payment	Use	1.637%	100.00%

Note(s): Use a PCA model and predict the index

Source(s): Authors' elaboration

structural and sociodemographic conditions that affect their adoption. The interaction between users and providers within the digital financial ecosystem is key for technological transformation to effectively reduce access and use gaps in the region.

6. Discussion

6.1 Theoretical implications

The findings support key theoretical frameworks in DFI. The study aligns with the digital agent theory of financial inclusion, emphasizing the interaction between financial service providers and users in facilitating adoption (Ozili, 2024). The study results confirm that sociodemographic factors significantly shape financial service adoption, reinforcing the need for user-centered fintech innovations that lower entry barriers.

The positive correlation between fintech penetration and DFI demonstrates how a well-developed digital financial infrastructure enhances access, supporting the notion that broader systemic forces shape financial inclusion.

Table 9. Regression estimates between DFI index and determinants

Variables	DFI index (1)	DFI index (2)	DFI index (3)	DFI index (4)
LifeCycle: 18–25 years old	−0.135	−0.326***	−0.322***	−0.369***
	(0.114)	(0.107)	(0.105)	(0.0983)
LifeCycle: 26–35 years old	−0.389***	−0.440***	−0.420***	−0.524***
	(0.112)	(0.105)	(0.103)	(0.0967)
LifeCycle: 36–49 years old	−0.656***	−0.562***	−0.641***	−0.821***
	(0.118)	(0.113)	(0.111)	(0.104)
LifeCycle: 50–64 years old	−1.207***	−0.954***	−1.068***	−1.298***
	(0.148)	(0.142)	(0.140)	(0.131)
LifeCycle: Over 65 years old	−0.501	−0.396	−0.323	−0.433
	(0.459)	(0.425)	(0.418)	(0.390)
Female	−0.557***	−0.541***	−0.458***	−0.402***
	(0.0711)	(0.0662)	(0.0654)	(0.0611)
Is in the workforce?	0.706***	0.552***	0.532***	0.457***
	(0.106)	(0.0985)	(0.0969)	(0.0904)
Secondary school completed		1.499***	1.311***	1.018***
		(0.103)	(0.103)	(0.0968)
Tertiary education or more completed		2.666***	2.267***	2.030***
		(0.108)	(0.112)	(0.105)
Income level: Quin2			0.141	0.153
			(0.149)	(0.139)
Income level: Quin3			0.345**	0.398***
			(0.145)	(0.135)
Income level: Quin4			0.790***	0.783***
			(0.135)	(0.126)
Income level: Quin5			1.127***	1.093***
			(0.133)	(0.124)
Country category: 2				−0.809***
				(0.0843)
Country category: 1				0.981***
				(0.0717)
Constant	0.0813	−1.435***	−1.928***	−1.840***
	(0.139)	(0.159)	(0.186)	(0.177)
Observations	3,952	3,920	3,920	3,920
R-squared	0.064	0.196	0.224	0.326

Note(s): Standard errors are in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Column (1) shows the results of a regression between the index and life cycle, gender and employment, while columns (2), (3) and (4) exhibit the same probit model with other control variables, namely education, income level and country category, being included in the model in that order. The country category groups countries according to fintech market penetration in each nation
Source(s): Authors' elaboration

6.2 Managerial implications

From a practical perspective, these findings provide valuable guidance for policymakers, fintech companies and financial institutions. The persistent gender gap in DFI highlights the urgent need for tailored strategies that encourage more women to engage in digital finance. This could include financial literacy programs, fintech solutions designed with gender inclusivity in mind and regulatory frameworks that ensure equitable access to financial services.

At the same time, improving digital literacy and accessibility for older adults and lower-income populations is essential for making fintech solutions genuinely inclusive. Many people in these groups face barriers to adoption, whether due to a lack of familiarity with digital tools or limited access to reliable internet and mobile banking services. Authorities should establish public and private incentives to reach populations most excluded from these digital financial services, including people of advanced age, women, and individuals with lower levels of education and income, and countries without the adoption of fintech companies.

Moreover, the positive relationship between fintech market penetration and financial inclusion suggests that governments and regulatory bodies should create a more supportive environment for fintech innovation. Reducing barriers to entry, encouraging competition among financial service providers and promoting policies that expand access will be key to ensuring that digital financial services effectively reach underserved communities.

6.3 Limitations and future research agenda

This study has several limitations. It focuses on sociodemographic factors, excluding other relevant aspects such as digital infrastructure, regulatory frameworks and cultural barriers, which can play a key role in DFI. On the other hand, measuring DFI through the selected indicators may not fully reflect the region's diversity of emerging financial services and models. A further limitation lies in the reliance on the Global Findex Database, which may be subject to potential biases such as self-reporting inaccuracies, possibly affecting the accuracy and representativeness of the results. Additionally, it should be noted that 2021 was the first year in which the Global Findex survey included questions on DFI, which restricts the possibility of conducting a deeper historical or longitudinal analysis. These limitations open opportunities for future research incorporating longitudinal approaches, qualitative analyses and a deeper evaluation of the impact of public policies and fintech strategies on adopting digital financial services. Moreover, it is essential to study the effectiveness of private and public initiatives in promoting a higher level of financial inclusion and whether these initiatives specifically target people less likely to access and use digital financial products.

7. Conclusions

This study examines the determinants of DFI in Latin America, confirming that fintech penetration is a key factor in improving access to financial services. Countries with a higher presence of fintech companies show higher levels of financial inclusion, as these firms reduce barriers through user-friendly digital platforms. This aligns with Demir *et al.* (2022), who highlight that mobile payments and online platforms expand financial access, particularly for individuals excluded from the formal banking system.

The main findings indicate that sociodemographic factors are crucial determinants when assessing DFI and have a statistically significant relationship in the applied models. This relationship can be negative or positive, depending on the nature of the factors. Unambiguously, the results show a positive relationship between DFI and the age ranges of young men with employment, as well as variables such as higher levels of education and income and countries with a higher level of fintech company penetration.

The results likewise reveal persistent gender disparities in DFI. Women are considerably less likely to access and use digital financial services, supporting the study by Ali (2023), who found that men are more likely to adopt digital banking. This reinforces the need for targeted financial literacy programs and inclusive fintech solutions to close the gender gap.

Similarly, age plays a crucial role, with younger individuals showing higher levels of DFI, consistent with technology adoption trends. This is in line with prior studies suggesting that younger generations engage more with digital finance due to their familiarity with technology. In the same way, education and employment status significantly impact financial inclusion. Individuals with higher education levels are more likely to access digital financial services, confirming the results of Liu *et al.* (2021), who found that education enhances financial access in rural China. Likewise, employment and income levels are positively associated with financial inclusion, as employed individuals and those with higher earnings engage more actively in financial services (Motta and Gonzalez Farias, 2022).

An unexpected result is the role of low-income populations in DFI. While fintech technology seeks to reduce exclusion, many low-income people continue to turn to informal financial solutions due to a lack of digital products suitable for their needs. This phenomenon, known as digital and connectivity exclusion, suggests that fintech alone is not enough to close financial gaps.

Supplementary material

The supplementary material for this article can be found online.

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