## Factors Associated with Financial Inclusion in Indonesia Before and During COVID-19: Evidence from Global Findex Data

Puguh Prasetyoputra <sup>1,\*</sup>, Yovita Isnasari <sup>2</sup>, Ari Purwanto Sarwo Prasojo <sup>1</sup>, Iwan Hermawan <sup>2</sup>

<sup>1</sup>Research Center for Population, National Research and Innovation Agency (BRIN), Indonesia <sup>2</sup>Research Center for Economics of Industry, Services, and Trade, National Research and Innovation Agency (BRIN), Indonesia

Abstract This study examines the factors associated with financial inclusion and the use of financial technology (FinTech) in Indonesia, both before and during the COVID-19 pandemic, using the Global Findex data from 2017 and 2021. Multivariable logistic regression models were fitted to analyze the factors associated with formal account ownership, savings, borrowing, mobile/Internet payments, and mobile money services usage. The results suggest that formal account ownership remained stable, whereas savings and borrowing declined during the pandemic. Education was observed as a variable with a significant correlation with financial inclusion and the use of FinTech. Higher income and mobile phone ownership significantly increased the likelihood of inclusion for all the indicators. Female individuals have a higher probability of owning a formal account and saving in one than males. Moreover, the pandemic accelerated the adoption of digital financial services. Policy recommendations include: 1) strengthening financial and digital literacy programs, especially for underserved groups; 2) expanding affordable digital infrastructure; 3) developing gender-responsive financial products; 4) balancing FinTech innovation with consumer protection; and 5) leveraging public-private partnerships to scale digital payment ecosystems. Future research should examine the long-term impacts on household resilience and explore the behavioral factors influencing inclusion beyond socioeconomic variables.

Keywords financial inclusion, mobile money, digital payment, COVID-19 pandemic, Indonesia

AMS 2010 subject classifications 62H15, 62H20

**DOI:** 10.19139/soic-2310-5070-2852

#### 1. Introduction

Financial inclusion is crucial in addressing socioeconomic challenges and promoting sustainable development. Its implications extend beyond access to financial services and encompass a wide range of benefits that contribute to societal development. For instance, by fostering gender equality, financial inclusion empowers women economically, increasing their involvement in the formal economy and to make independent financial decisions [1, 2]. This benefit, in turn, leads to better social welfare and enhanced employment opportunities, particularly for marginalized groups [3, 4]. Moreover, financial inclusion is useful for poverty reduction [5, 6, 7], providing individuals and communities with the means of saving, investing, and building financial resilience [8, 9].

The far-reaching impacts of financial inclusion extend to fostering economic equality, growth, and development [10, 11, 12, 13]. Providing access to formal financial services enables individuals and firms to become more involved in the economy, thus stimulating entrepreneurship and innovation. These comprehensive positive effects of financial inclusion show that it acts as a catalyst for Sustainable Development Goals (SDGs), particularly SDG 1 (poverty), SDG 5 (gender equality), SDG 8 (decent work and economic growth), and SDG 9 (industry)

<sup>\*</sup>Correspondence to: Puguh Prasetyoputra (Email: pprasetyoputra@gmail.com). Research Center for Population, National Research and Innovation Agency (BRIN), Jl. Jend. Gatot Subroto Kav. 10, South Jakarta 12710, Special Region of Jakarta, Indonesia.

[14, 15, 16]. Thus, increasing financial inclusion benefits individuals and communities and is vital for achieving broader sustainable development objectives on a global scale.

Despite the aforementioned benefits of financial inclusion, an estimated 1.4 billion people worldwide were unbanked in 2021, according to the World Bank's Global Financial Inclusion (Global Findex) database [17], which means they do not have access to an account under a formal financial institution or a mobile money provider [18]. Hence, these individuals face major challenges in accessing basic financial services such as savings, payments, credit, and insurance [19]. These underserved populations may miss out on many social and economic opportunities that may improve their lives and well-being. The unbanked people cite a lack of money or financial services too expensive [17].

Increasing access to digital financial services is considered an effective way to enhance financial inclusion. However, persistent inequalities in access to and usage of digital financial services still exist [20, 21, 22]. The current situation is better than it was in the past decade. However, the growth in financial account ownership is not equal for everyone, with women, the less affluent, and the less educated lagging behind their better-off counterparts [17]. Moreover, the state of financial inclusion differs across regions. There are more than 300 million unbanked people in Southeast Asia, with almost one-third of them residing in Indonesia, the world's fourth most populous country [17, 23, 24].

The COVID-19 pandemic has wreaked havoc on the health systems of hundreds of countries worldwide [25]. Many countries imposed strict lockdowns to curb the spread of the virus. Consequently, the economy slowed significantly, resulting in numerous adverse economic and social implications for the livelihoods of millions [26]. However, the pandemic has profoundly impacted financial inclusion in Southeast Asia, creating both opportunities and challenges. One significant positive effect was the rapid uptake of digital financial services, such as online and mobile banking, which was spurred by social distancing and lockdowns [27, 28, 29]. This change in consumer habits has led to a greater dependence on digital transactions, with factors such as perceived ease of use, usefulness, and trust, along with government backing, promoting financial technology (FinTech) adoption even among those with lower financial literacy in countries such as Vietnam [30, 31]. Additionally, financial inclusion is crucial in offering essential financial products and services, such as capital mobilization and lending at reasonable rates, which is especially important during the pandemic [31].

In addition to the aforementioned issues related to financial inclusion, access to financial services in Indonesia was considered low compared to other Asian countries before the COVID-19 pandemic. In 2014, the rate was 36.1%, which was lower than the 80.7% in Malaysia, 78.1% in Thailand, and the East Asia and Pacific average of 69% [32]. As such, financial inclusion in Indonesia has received attention from researchers, many of whom have used the Global Findex Database. Nugroho and Purwanti [33] and Susilowati and Leonnard [34] analyzed Indonesia's 2014 Global Findex data to investigate the determinants of financial inclusion in Indonesia. Susilowati et al. [35] utilized a more recent round, the 2017 Global Findex, to investigate the impact of income, education, gender, and age on the three primary indicators of financial inclusion (bank account ownership, savings behavior, and borrowing from a formal financial institution) in Indonesia. Esquivias et al. [36] analyzed the 2017 Global Findex data of Vietnam, Indonesia, and the Philippines to evaluate how individuals access both formal and informal financial services, as well as savings and credit options, while taking into account their socio-economic characteristics. Khusniati and Yusuf [37] used the latest round of the Global Findex (2021) to investigate the influence of gender and women's employment status on mobile phone use for in-store financial transactions in Indonesia.

Moreover, some studies used multiple datasets. Shrestha and Nursamsu [38] combined data from the Indonesian Family Life Survey (IFLS) and the 2011, 2014, and 2017 rounds of the Global Findex database. They examined the relationship between financial inclusion and household savings in Indonesia. Finally, Putri and Nurhayati [39] analyzed data from the 2014, 2017, and 2021 rounds of the Global Findex database. They examined whether financial inclusion improves financial literacy in selected ASEAN countries (Indonesia, Malaysia, Singapore, Thailand, the Philippines, Myanmar, and Cambodia). However, they did not consider the context of the COVID-19 pandemic in their study.

Studies that used data from the Global Findex database and focused on the relationship between the COVID-19 pandemic and financial inclusion have also been conducted. Dluhopolskyi et al. [40] analyzed the Global Findex

data from multiple countries, including Indonesia, to compare the conditions before and during the COVID-19 pandemic. However, the changes that may be attributable to the pandemic may differ when a within-country subset is analyzed because of differing sociodemographic characteristics. Moreover, Mabrouk et al. [41] employed Global Findex data to examine financial inclusion before and during the COVID-19 pandemic. However, they focused only on Saudi Arabia.

Like hundreds of other countries, Indonesia was heavily affected by the COVID-19 pandemic. President Joko Widodo announced the first two confirmed cases of COVID-19 on 2nd of March 2020 [42]. Then on 31st of March the same year, the Government of Indonesia (GoI) enacted the Big Scale Social Restriction (*pembatasan sosial berskala besar* or PSBB) policy to accelerate the mitigation of COVID-19 Eradication [43]. This restriction gave a big push to people and entrepreneurs to shift to digital payment platforms [44]. Moreover, the distribution of social protection program benefits from the GoI was done through electronic bank transfers [45, 46, 47]. These factors are believed to influence financial inclusion.

Despite extensive previous research on financial inclusion in Southeast Asia, particularly in Indonesia, there remains limited evidence of progress in financial inclusion in Indonesia before and during the COVID-19 pandemic. Therefore, we aim to fill this gap by utilizing data from the Global Findex database for Indonesia from 2017 to 2021 [48, 49].

This study makes two contributions to the literature. First, we provide evidence of financial inclusion and the use of FinTech before and during the pandemic. Second, we provide recent information on sociodemographic factors associated with financial inclusion and the use of FinTech in Indonesia. Understanding these factors can help policymakers design policies to address the inequalities related to financial inclusion and the use of FinTech in Indonesia. Our results suggest that saving and borrowing behaviors during the pandemic were lower than they had been prior to the pandemic. In contrast, the use of mobile phones and the Internet for making payments, as well as mobile money services, increased during the pandemic compared to before. The remainder of this paper is organized as follows. The next section provides a brief description of the data sources, variables, and econometric analyses employed in this study. The following section presents and discusses the main empirical findings. The final section concludes and provides recommendations.

## 2. Methodology

#### 2.1. Theoretical Considerations

Although this study draws data from a secondary data source, from which we can only select information or variables that are collected and disclosed to the public, our analyses were influenced by several theories related to financial inclusion. The first theory is the Vulnerable Group Theory of Financial Inclusion, which posits that "financial inclusion efforts should be targeted to all vulnerable people in society" [50, 51]. Here, 'vulnerable' refers to the state of being physically or emotionally disadvantaged due to certain events or decisions made by actors such as the government, institutions, or individuals [51]. Ozili [52] argues that providing vulnerable people with financial services enables them to access financial resources that can be used to improve their welfare. Therefore, we included explanatory variables related to socioeconomic position, as a proxy for vulnerability, such as the highest educational attainment and income. We also included the sex of the individual as an explanatory variable, as there may be gender-related disparities in financial inclusion and the use of FinTechs.

Another relevant theory that we benefit from is the Technology Acceptance Model (TAM), which posits that the adoption of new technologies (i.e., FinTech) is mainly determined by two factors [53]: (1) perceived usefulness, the extent to which an individual believes that utilizing a specific system will improve their job performance or life; and (2) perceived ease of use, the extent to which an individual perceives that utilizing a specific system will require minimal effort. The relationship between the first factor and the COVID-19 pandemic is that the pandemic would increase such factors; the physical distancing caused by the pandemic made digital payments, e-commerce,

<sup>&</sup>lt;sup>1</sup>page 402 of Ozili [51].

and online lending crucial for sustaining life during the pandemic. Moreover, innovations in digital payments, both before and during the pandemic, have reduced the need to use such methods.

This study also includes FinTech adoption. Studies have shown that the COVID-19 pandemic is associated with an increase in FinTech adoption in small and medium enterprises (SMEs) [54, 55] and individuals [56, 57]. The first two studies applied the Diffusion of Innovations theory formulated by Everett M. Rogers [58]. This theory suggests that the rate of adoption of certain innovations (i.e., FinTech) may be explained by the characteristics of such innovations, as perceived by individuals. There are five perceived characteristics [58]:<sup>2</sup> (1) relative advantage, the degree to which an innovation is perceived as better than the idea it supersedes; (2) compatibility, the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters; (3) complexity, the degree to which an innovation is perceived as difficult to understand and use; (4) trialability, the degree to which an innovation may be experimented with on a limited basis; and (5) observability, the degree to which the results of an innovation are visible to others.

These perceived characteristics, although not directly assessed in this study, can help explain the role of the pandemic in inducing FinTech adoption. For instance, relative advantage; in the context of the pandemic, the use of FinTech for payment of goods and services has an obvious advantage over using cash, which prevents direct contact with the sellers and thus reduces the risk of contracting the COVID-19 virus. Another relevant characteristic is complexity; people with higher educational attainment may be better equipped to use more complex technologies and are therefore more likely to adopt FinTech.

#### 2.2. Data Source

We utilized data from the Global Findex database, a survey conducted by Gallup, Inc., in conjunction with its annual Gallup World Poll, in 148 countries. The survey has been conducted every three years since 2011. When this article was written, the latest one was conducted in 2021, owing to the COVID-19 pandemic. The collected information comprises financial access, the use of financial services, and financial well-being [17, 59].

In this study, we utilized the Indonesian subset of the 2017 round to represent the conditions prior to the COVID-19 pandemic and the 2021 round to represent the conditions during the pandemic [48, 49]. The datasets are publicly available upon request at "Global Findex 2017" and "Global Findex 2021". Both rounds in Indonesia were conducted through face-to-face interviews. The interviews for the 2017 round were conducted from April 10 to May 20, 2017. The interviews for the 2021 round were conducted from July 7th to October 15th, 2021.

## 2.3. Study Sample

The 2017 round covers 1,000 nationally representative people aged 15 years and above, and the 2021 round covers 1,062 people. More details on these surveys can be found in the 2017 and 2021 reports [17, 59]. These two subsets were processed and cleaned separately. Then, we appended them and added a dummy variable indicating the survey round (0 = '2017 – before the pandemic', 1 = '2021 – during the pandemic'). For four of the five dependent variables, the complete samples were 1000 and 1062 individuals, respectively. However, there are additional missing observations as the fourth dependent variable (i.e., using mobile phones or the Internet to make payments) is only asked when the individual has an account at a financial institution, a mobile money account, or both (Figure 1). We used unweighted samples in the figure because we intend to show the skip pattern of one dependent variable.

## 2.4. Ethics Statement

This study is a further analysis of datasets available upon request at <a href="http://microdata.worldbank.org">http://microdata.worldbank.org</a>. The World Bank has removed any information that could be used to identify the respondents. Therefore, no additional ethical clearance was required.

<sup>&</sup>lt;sup>2</sup>On page 15 of Rogers [58].

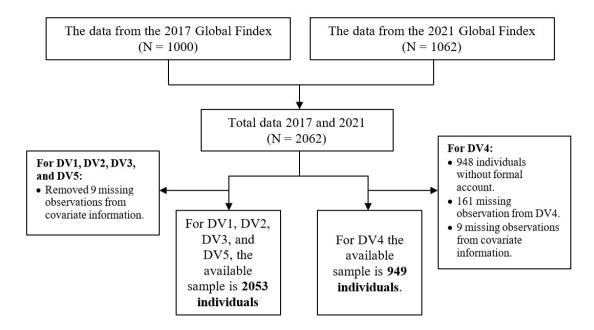


Figure 1. Flow diagram of the sample selection (unweighted sample).

## 2.5. Dependent Variables

This study has five dependent variables: formal account ownership, borrowing, saving, using mobile phones or the Internet to pay, and using mobile money services, all of which are dummy variables. The first three factors represent financial inclusion, and the other two represent FinTech. All these variables are interrelated [17]. A formal account serves as an entry point to additional financial services, making it a crucial indicator of financial inclusion [17, 10]. Access to formal credit and savings can improve people's welfare, thereby deepening financial inclusion [60, 61, 62]. Moreover, the FinTech variables are included because they are known to enhance traditional financial inclusion measures (i.e., formal accounts, savings, and credit) [63, 64]. Furthermore, studies have shown that FinTech enables people to make transactions without direct reliance on traditional banking infrastructure [65, 66]. Therefore, all five variables were included to obtain a comprehensive understanding of financial inclusion in Indonesia.

Table 1 presents the definitions of the variables used in this study. Financial inclusion is represented by whether an individual has an account at a financial institution or mobile money.<sup>3</sup> Borrowing refers to whether "the respondent, personally or together with someone else, borrowed money in the past year, including from a bank or similar financial institution, via a mobile money account, from family or friends, from an informal savings group, or for any other reason" [17, 67].<sup>4</sup> Saving refers to whether "the respondent personally saved or set aside money in the past year, including using an account at a financial institution, a mobile money account, a savings club, a person outside the family, or for any reason" [17, 67].<sup>5</sup> We also assessed the use of mobile phones or the internet to make payments. Finally, mobile money service use is represented by whether an individual used "mobile money services to pay bills or to send or receive money in the past year" [17, 67].<sup>6</sup>

<sup>&</sup>lt;sup>3</sup>The definition does not include "non-bank financial institutions such as pension funds, retirement accounts, insurance companies, or equity holdings such as stocks" [17, 67].

<sup>&</sup>lt;sup>4</sup>on page 2 of [67].

<sup>&</sup>lt;sup>5</sup> on page 2 of [67].

<sup>&</sup>lt;sup>6</sup> on page 2 of [67].

This study has five dependent variables: formal account ownership, borrowing, saving, using mobile phones or the Internet to pay, and using mobile money services, all of which are represented as binary variables. The first three represent financial inclusion, and the other two represent FinTech. Table 1 presents the definitions of the variables used in this study. Financial inclusion is represented by whether an individual has an account at a financial institution or mobile money. Borrowing refers to whether "the respondent, personally or together with someone else, borrowed money in the past year, including from a bank or similar financial institution, via a mobile money account, from family or friends, from an informal savings group, or for any other reason" [17, 67]. Saving refers to whether "the respondent personally saved or set aside money in the past year, including using an account at a financial institution, a mobile money account, a savings club, a person outside the family, or for any reason" [17, 67]. Mobile money service use is represented by whether an individual uses "mobile money services to pay bills or to send or receive money in the past year" [17, 67]. Finally, we assessed the use of mobile phones or the Internet to make payments. Table 1 presents the dependent and explanatory variables used in this study.

## 2.6. Explanatory Variables

We selected the explanatory variables based on previous studies [24, 33, 34, 36, 41, 60, 65, 68, 69, 70, 71, 72] and whether they were available from the 2017 and 2021 survey rounds. Our explanatory variables include gender, age, highest education, income, employment status, mobile phone ownership, and survey year. Gender is a binary variable. Age is measured in years, but we also included its quadratic term to capture the nonlinear relationship with financial inclusion [71]. For education and income, we used the categorization provided by the Global Findex data and the respective reference categories from previous studies [24, 72, 73]. We use five quintiles for income. Employment status, mobile phone ownership, and survey year are dummy variables. Moreover, unlike the 2017 and 2021 reports of the Global Findex survey, which coded "Do not know" and "Refused to answer" as "No," we coded these two types of responses as missing observations.

Table 1. Description of the variables

Variables	Description	Code
Dependent variables – Main indic	cators of Financial Inclusion	
Has a financial account or mobile money	A dummy variable equals to one if currently has an account at a formal institution or mobile money, zero otherwise.	account
Has saved money in the past year	A dummy variable equals to one if saved using an account at a formal institution in the past 12 months, zero otherwise.	saving
Has borrowed money in the past year	A dummy variable equals to one if the respondent borrowed from a formal institution in the past 12 months, zero otherwise.	credit

Continued on next page

<sup>&</sup>lt;sup>7</sup>The definition does not include "non-bank financial institutions such as pension funds, retirement accounts, insurance companies, or equity holdings such as stocks" [17, 67].

<sup>&</sup>lt;sup>8</sup>Mobile money service providers are those listed in the GSM Association's Mobile Money for the Unbanked (GSMA MMU) database [17, 67].

Table 1 – continued from previous page

Variables	Description	Code
Used mobile phone or internet to make payments	A dummy variable equals to one if the respondent has used a mobile phone or the Internet to make payments, buy things, or to send or receive money from or to their financial institution account (excluding mobile money accounts) in the past year, zero otherwise. This variable was assessed only for those who reported having a formal financial account or debit card.	mobintpay
Used mobile money services	A dummy variable equals to one if the respondent used mobile money services to pay bills or to send or receive money in the past year, zero otherwise.	mmoney
Explanatory variables		
Gender	A dummy variable equals to one if the respondent is a female, zero otherwise.	female
Age	Age of respondent in number of years.	age
Age-squared	Quadratic term of age.	age*age
Highest education:		
Primary or less	A dummy variable equals to one if the respondent's highest education is primary education, zero otherwise.	educ3c_1
Secondary	A dummy variable equals to one if the respondent's highest education is secondary education, zero otherwise.	educ3c_2
Tertiary or higher	A dummy variable equals to one if the respondent's highest education is tertiary education, zero otherwise.	educ3c_3
Currently employed	A dummy variable equals to one if currently respondent is currently employed, zero otherwise.	employed
Income quintile group:		
Income-lowest 20%	A dummy variable equals to one if income is in the first income quintile, zero otherwise.	income5_1
Income-second 20%	A dummy variable equals to one if income is in the second income quintile, zero otherwise.	income5_2
Income-third 20%	A dummy variable equals to one if income is in the third income quintile, zero otherwise.	income5_3
Income-fourth 20%	A dummy variable equals to one if income is in the fourth income quintile, zero otherwise.	income5_4
Income-highest 20%	A dummy variable equals to one if income is in the fifth income quintile, zero otherwise.	income5_5
Owns a mobile phone	A dummy variable equals to one if the respondent owns a mobile phone, zero otherwise.	mphone

Continued on next page

Variables	<b>Description</b> Cod	de
Survey round	A dummy variable equals to one if the survey round is 2021 (during the pandemic), zero if the survey round is 2017 (before the pandemic).	ar2c

Table 1 – continued from previous page

Source: The 2017 and 2021 Global Findex Survey [17, 59, 67].

## 2.7. Model Specification

Since our dependent variables are binary, we employ multivariable logistic regression analysis to examine the changes in the use of financial inclusion indicators and FinTech use in Indonesia. The logistic model, estimated using the maximum likelihood techniques, was applied to all five models. We included a survey year dummy variable to examine the changes in the dependent variables during the COVID-19 pandemic compared with the previous situation.

Let  $Pr(y_i = 1|x_i)$ , which can be denoted as  $P_i$  for brevity, be the probability that the dependent variable  $y_i$  is 1 (i.e., account, saving, credit, mobintpay, or mmoney) for individual i, given their vector of covariates  $x_i$ . The estimated logistic regression is as follows [74]:

$$\log\left[\frac{P_i}{1-P_i}\right] = b_0 + b_1 female_i + b_1 age_i + b_2 age_i^2 + b_3 educ\_secondary_i + b_4 educ\_tertiary_i + b_5 income\_q_2 + b_6 income\_q_3 + b_7 income\_q_4 + b_8 income\_q_5 + b_9 mphone_i + b_{10} year_i$$

$$(1)$$

where  $b_0$  is the intercept,  $b_1$  to  $b_10$  are the estimated coefficients, and  $\varepsilon_i$  are the residuals.

## 2.8. Estimation Strategy

The coefficients obtained from fitting logit regression models are difficult to interpret directly and are not substantively meaningful for many people [75]. However, there are ways to make the coefficients more interpretable. One is to exponentiate both sides of the equation to obtain the following:

$$\frac{P_i}{1 - P_i} = \exp(b_0) \times \exp(b_1) female_i \times \exp(b_1) age_i \times \exp(b_2) age_i^2 \times \exp(b_3) educ\_secondary_i \times \exp(b_4) educ\_tertiary_i \times \exp(b_5) income\_q_{2i} \times \exp(b_6) income\_q_{3i} \times \exp(b_7) income\_q_{4i} \times \exp(b_8) income\_q_{5i} \times \exp(b_9) mphone_i \times \exp(b_{10}) year_i$$
(2)

where the left-hand side of the equation  $(\frac{P_i}{1-P_i})$  gives the fitted odds of success (i.e., the dependent variable is coded as 1). The exponentiated coefficients then become the odds ratios (ORs), which can be interpreted as follows: for a unit change in the explanatory variable  $(x_k)$ , the odds are expected to change by a factor of  $\exp(b_k)$ , holding other explanatory variables constant [75]. If  $\exp(b_k) > 1$ , the association is positive, whereas if  $\exp(b_k) < 1$  the association is negative.

However, although ORs have been widely used to represent associations in multivariable regression, they have several limitations. First, ORs are often interpreted synonymously with relative risks (also known as risk ratios or RRs) by researchers, the media, and the general public, even though they are not the same [76, 77]. Relative risk is the ratio of the probability of an outcome in an exposed group to the probability of the outcome in an unexposed group. This misinterpretation becomes a potential problem when the baseline risk or treatment effect increases, leading to exaggeration of the OR, making the association appear stronger than it really is [76, 77, 78, 79].

The second limitation is still related to the interpretation of OR, which is not as intuitive as risks or probabilities, as it does not indicate how big the probability (magnitude) of an outcome changes [75]. This problem becomes

more pronounced when the reference category of the explanatory variable is switched, causing OR < 1 to change to OR > 1 and vice versa, making it more difficult to understand, especially for policymakers or the broader public. Finally, conditional ORs are non-collapsible, which means that their magnitude can change depending on which other variables are included in the model, even if those covariates are uncorrelated with the main variables of interest [80, 81, 82]. This characteristic makes it difficult to compare ORs across different models. Based on these three reasons, we opted for an alternative measure of association, namely average marginal effects (AMEs), which has the following advantages over ORs:

- AMEs address the misinterpretation of ORs as RRs.
- AMEs provide a direct measure of the change in probability, which is easier for non-expert audiences to understand and more closely reflects real-world differences.
- AMEs are generally more comparable across models, as their magnitudes are less affected by adding or removing covariates that are uncorrelated with the predictor of interest.

AME is the mean of the marginal effect computed at the observed values for all observations in the estimation sample [75]. For a marginal (infinitesimal or incremental) change in the continuous predictor  $x_k$ , the AME is the average of the partial derivatives for each individual:

$$AME_{x_k} = \frac{1}{N} \sum_{i=1}^{N} \frac{A \Pr(y_i = 1 | x = x_i)}{Ax_k}$$
(3)

For a discrete change in a predictor  $x_k$  (e.g., a dummy variable changing from 0 to 1, or a change from *start-value* to *end-value*), the AME is the average of the individual-level changes in probability:

$$AME_{\Delta x_k} = \frac{1}{N} \sum_{i=1}^{N} [\Pr(y_i = 1 | x_i, x_k = \text{end}) - \Pr(y_i = 1 | x_i, x_k = \text{start})]$$
 (4)

This can be interpreted as follows: on average, changing  $x_k$  from *start-value* to *end-value* increases/decreases the probability of the outcome by [AME value], holding all other variables constant.

All data processing and analyses were performed using R version 4.3.3 [83]. We estimated the models using multivariable binary logistic regression by incorporating the survey design with the "svyglm" function from the "survey" package [84, 85]. We used normalized survey weights (where the sum of weights equals the sample size per wave) for the regression analyses and specified the survey design as independent (i.e., set ids = 1 in the "svydesign" function). This approach simplified the sampling design of the Global Findex survey because the World Bank does not provide the identifiers for primary sampling unit (PSU) and strata in the publicly accessible data sets. We also applied a global design effect (Deff) adjustment to the covariance matrix, as per the official documentation [86, 87].

The models related to the four dependent variables (*account*, *saving*, *credit*, and *mmoney*) were fitted on complete-case data because the missing values for "has account or debit" and "own a mobile phone" are very small (see Table 3) (Newman, 2014). However, we conducted multiple imputations for the model with "used mobile phone or internet to make payments" as the dependent variable since the proportion of missing values was approximately 21% for 2017 and 13% for 2021 (see Table A1 in the Appendix). The missing values were generated from the response answer "don't know" or "refused to answer," hence this is not a missing completely at random (MCAR) type. We also tested using logistic regression and found evidence that the probability of missing values was dependent on explanatory variables (see Table A2 in the Appendix).

Imputation was conducted for each survey round using logistic regression with all explanatory variables and the natural logarithm of the survey weight as predictors. We set 30 (m) imputations since the maximum missing value is 21%. Van Buuren [88]<sup>9</sup> argues that the number of repetitions for multiple imputation can be set to the average

<sup>&</sup>lt;sup>9</sup>page 61 of Van Buuren [88].

percentage of missing, and the substantive conclusions are unlikely to change as a result of raising the number of repetitions. We then fit the regression model for each dataset from imputation and inferred the results using Rubin's rules [89, 90]. These were done using "mice" [91] and "mitools" package [92].

As mentioned earlier, the results were presented using AME for several reasons and to facilitate easier interpretation. AME was calculated using "avg\_slopes" from the "marginaleffects" package [93]. We assessed the statistical significance of the estimated AMEs at four levels: 10%, 5%, 1%, and 0.1%. To assess the goodness-of-fit (GoF), we used Tjur's coefficient of determination (Tjur  $R^2$ ), which was estimated using the "performance" package [94, 95]. The Tjur  $R^2$  is formulated as follows:

$$D = \bar{\hat{p}}_1 - \bar{\hat{p}}_0 \tag{5}$$

where  $\bar{p}_1$  and  $\bar{p}_0$  denote the weighted averages of the fitted values for success (i.e.,  $\Pr(y_i=1|x_i)$ ) and failure (i.e.,  $\Pr(y_i=0|x_i)$ ), respectively. One can refer to Tjur [95] for a more detailed discussion of why Tjur  $R^2$  or D is a good substitute for the conventional pseudo  $R^2$  in logistic regression models. Furthermore, to assess the GoF of the estimated models, we also estimated the "area under the receiver operating characteristic (ROC) curve" statistics (henceforth AUC), which were produced using the "WeightedROC" package [96]. The area under the ROC, spanning from 0.5 to 1.0, serves as an indicator of the logistic regression model's capability to distinguish between individuals who experience the outcome of interest (i.e.,  $\hat{\mu}(x)=1$ ) and those who do not (i.e.,  $\hat{\mu}(x)=0$ ) [74]. We assessed the estimated AUCs based on a guideline or rule of thumb proposed by Fox and Weisberg [74]:

$$\begin{cases} & \text{ROC} = 0.5 & \text{Considered as no discrimination, similar to a coin toss.} \\ & 0.5 < \text{ROC} < 0.7 & \text{Considered as a poor discrimination, not much better than a coin toss.} \\ & 0.7 \le \text{ROC} \le 0.8 & \text{Considered as an acceptable discrimination.} \\ & 0.8 \le \text{ROC} < 0.9 & \text{Considered as an excellent discrimination.} \\ & \text{ROC} \ge 0.9 & \text{Considered as an outstanding discrimination.} \end{cases}$$

To address possible collinearity issues, we assessed the generalized variance inflation factor (GVIF) using the "car" package [74, 97, 98]. Although no clear-cut answers exist to how large a GVIF value we need to worry about, there are some expert guidelines [99]. Allison [100] suggested that values of 2.5 may be of concern for continuous or binary variables, and values above 5 or 10 indicate a more serious collinearity problem. However, if the explanatory variable is categorical (has more than two categories), one should use another indicator, namely the adjusted generalized standard error inflation factor (aGSIF), which adjusts the GVIF by the degree of freedom (df). The aGSIF is equal to the square root of the GVIF for continuous variables and categorical regressors with two categories (df = 1) [99]. The aGSIF is expressed as follows:

$$aGSIF = GVIF^{\left(\frac{1}{2 \cdot df}\right)} \tag{6}$$

For aGSIFs, we consider values exceeding 1.6 to be potentially concerning, while those surpassing 2.2 or 3.2 suggest a more significant issue [99]. Nevertheless, these rules of thumb regarding the collinearity threshold are arbitrary and do not serve as strict requirements in modeling. Finally, when dealing with interactions in the model or multiple terms that define a polynomial, it is advisable to evaluate the VIFs or aGSIFs using a model that excludes interactions or higher-order polynomial terms [99, 100].

Table 2 presents the adjusted GVIF values from all the explanatory variables in all the five logistic regression models computed using the "car" package [74]. Regarding multicollinearity between explanatory variables, based on the aGVIF (or aGSIF), only age and age-squared variables had a GVIF value of over 5, which is considered high; however, the high GVIF is an expected characteristic of a variable and its polynomial (i.e., age and age-squared) and does not negatively affect the model's capacity to assess the overall impact of age [100].

Variables	Financial account	Borrowed in the past year	Saved in the past year	Paid using Mobile Phone or Internet <sup>1</sup>	Mobile Money Services
Female	1.09	1.06	1.07	1.12	1.23
Age	5.50	5.38	5.56	8.42	10.11
Age (years), squared	5.50	5.38	5.57	8.78	10.46
Highest education	1.07	1.06	1.08	1.11	1.11
Income quintile group	1.01	1.01	1.02	1.07	1.04
Currently in the workforce	1.09	1.08	1.10	1.12	1.25
Owns a mobile phone	1.09	1.09	1.12	1.57	1.43
Survey round	1.01	1.01	1.01	1.07	1.12

Table 2. Adjusted GVIF values from all five logistic regression models.

Note: GVIFs above are adjusted for degrees of freedom.

Source: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

## 2.9. Study Limitations

This study has several limitations. First, the Global Findex Surveys did not collect information on the province of residence. This variable may explain a substantial proportion of the probability of the dependent variables. Second, unlike the 2021 Global Findex Survey, the 2017 round did not collect information on respondents' areas of residence (urban or rural). Differences in infrastructure development between urban and rural areas may contribute to the penetration of Fintech in Indonesia. However, these potential differences could not be controlled in our study. Third, the publicly accessible datasets did not include primary sampling units (PSU) or strata identifiers, which precluded full design-based variance estimation. As a result, the analysis utilized normalized survey weights (where the sum of weights equals the sample size per wave) and applied a global design effect (Deff) adjustment to the covariance matrix, as per the official documentation. This approach provides a conservative correction, although it cannot fully account for the potential heterogeneity in clustering effects across regions or subpopulations. Moreover, the absence of geographical identifiers, such as provinces or districts, limited the ability to incorporate multilevel or spatial structures into the analysis. Consequently, the estimated parameters should be interpreted as representing national-level associations, rather than subnational variations. Robustness checks were performed to ensure that the substantive conclusions were not driven by these design-related limitations.

#### 3. Results and Discussion

This section provides a descriptive overview of the sample, presents the results of the logistic regression analyses, and discusses the empirical findings.

## 3.1. Descriptive Statistics

Table 3 presents the descriptive statistics for the pooled sample (N = 2,062) and for the separate 2017 (N = 1,000) and 2021 (N = 1,062) rounds. The analysis utilized weighted data to ensure that the statistics are representative of the target population. Based on the weighted total sample, females constituted 51.11% of the respondents. The mean age is 38.03 years, showing a slight increase from the 2017 round (mean = 37.27) to the 2021 round (mean = 38.75). Educational attainment has two dominant categories, with 47.49% of the sample reporting having primary

<sup>&</sup>lt;sup>1</sup>The GVIF values for Model 4 (Paid using Mobile Phone or Internet) were obtained from the maximum values of each explanatory variable in 30 models estimated from the multiple imputation.

education or less, and 47.84% having completed secondary education. A small percentage (4.68%) reported holding a tertiary degree education or higher. The majority of respondents (62.42%) were employed. As expected from the weighting procedure, the distribution of income quintiles was evenly distributed across the groups.

The main indicators of financial inclusion showed mixed results across the survey years. Overall, 50.35% of the weighted sample reported owning a formal account. This figure reflects a modest increase from 48.86% in 2017 to 51.76% in 2021. In contrast, other traditional financial indicators (i.e., formal savings and formal credit) declined. The percentage of formal savings decreased from 61.78% in 2017 to 49.08% in 2021. Similarly, the use of formal credit decreased from 54.84% in 2017 to 41.59% in 2021, indicating potential disruptions in traditional financial behavior due to economic uncertainties during the COVID-19 pandemic [30, 57, 101]. Such contractions are consistent with the finding that households faced income shocks and reduced borrowing due to tighter credit conditions during the pandemic [102, 103].

Indicators related to FinTech demonstrated low baseline adoption but showed significant growth. Mobile phone ownership, an important enabler of increased digital payments during the pandemic [104], was high at 75.21% for the total sample. Although it declined in 2021 to 73.40% compared to 77.15% in 2017. Despite high phone ownership, only 10.14% of the sample reported direct use of mobile phones or the Internet for payments. However, this indicator showed a significant increase, from 7.39% in 2017 to 12.62% in 2021. A similar trend is visible in mobile money services, where usage, while low overall (6.30%), nearly tripled from 3.12% in 2017 to 9.29% by 2021.

#### 3.2. Factors Associated with Main Financial Inclusion Indicators

We examined the factors associated with the main financial inclusion indicators. Table 4 presents the AMEs of the explanatory variables. All multivariable binary logit regression models were statistically significant (p < .001). The performance of the Formal Account and Savings models was acceptable (AUC > 0.70). In contrast, the Formal Credit model showed a weaker fit (AUC = 0.65), suggesting that unobserved factors, such as credit history or informal borrowing, may influence borrowing behavior. These findings are consistent with cross-country evidence showing that demographic and socioeconomic characteristics, such as education, income, and gender, are key determinants of financial inclusion [105].

In the Formal Account model, all variables were statistically significant, except for the survey round. Individuals who were female, had higher education, were in upper-income quintiles, were employed, and had mobile phones had a higher probability of owning a formal account. Moreover, we did not observe any statistically significant changes in account ownership during the COVID-19 pandemic. This finding suggests that account penetration may have reached a saturation point, with the pandemic affecting digital transaction volumes rather than account openings [17].

In the Formal Saving model, all explanatory variables were statistically significant. Individuals who were female, had higher education, were employed, and owned a mobile phone had a higher probability of formal saving. The statistically significant AMEs related to income quintiles highlight persistent income inequality [6]. The probability of Formal Saving declined during the pandemic by 11.7 percentage points, compared to before the pandemic, consistent with income shocks, rising consumption needs, and financial uncertainty [102, 103]. Despite stable account ownership, this decline suggests a shift towards short-term liquidity over long-term savings.

Stat., Optim. Inf. Comput. Vol. x, Month 202x

Table 3. Unweighted and Weighted Summary Statistics for Study Variables.

Variables		Unweighted		Weighted			
	Total	2017	2021	Total	2017	2021	
	(N=2,062)	(N=1,000)	(N=1,062)				
Main indicators of financial inclusion							
Formal account							
No	948 (45.97%)	467 (46.70%)	481 (45.29%)	(49.65%)	(51.14%)	(48.24%)	
Yes	1,114 (54.03%)	533 (53.30%)	581 (54.71%)	(50.35%)	(48.86%)	(51.76%)	
Formal saving							
No	861 (41.76%)	368 (36.80%)	493 (46.42%)	(44.76%)	(38.22%)	(50.92%)	
Yes	1,201 (58.24%)	632 (63.20%)	569 (53.58%)	(55.24%)	(61.78%)	(49.08%)	
Formal credit							
No	1,053 (51.07%)	442 (44.20%)	611 (57.53%)	(51.98%)	(45.16%)	(58.41%)	
Yes	1,009 (48.93%)	558 (55.80%)	451 (42.47%)	(48.02%)	(54.84%)	(41.59%)	
Financial technology							
Used mobile phone or internet to make							
payments							
Has account or debit: No	940 (49.58%)	459 (51.40%)	481 (47.96%)	(53.87%)	(56.35%)	(51.63%)	
Has account or debit: Missing	4 (0.21%)	4 (0.45%)	0 (0.00%)	(0.18%)	(0.37%)	(0.00%)	
No	748 (39.45%)	353 (39.53%)	395 (39.38%)	(35.82%)	(35.89%)	(35.76%)	
Yes	204 (10.76%)	77 (8.62%)	127 (12.66%)	(10.14%)	(7.39%)	(12.62%)	
Missing	166 (8.10%)	107 (11.00%)	59 (5.60%)	(8.50%)	(11.00%)	(6.60%)	
Used mobile money services in the last 12 months							
No	1,932 (93.70%)	961 (96.10%)	971 (91.43%)	(93.70%)	(96.88%)	(90.71%)	
Yes	130 (6.30%)	39 (3.90%)	91 (8.57%)	(6.30%)	(3.12%)	(9.29%)	
Explanatory variables							
Female							
No	853 (41.37%)	393 (39.30%)	460 (43.31%)	(48.89%)	(48.88%)	(48.90%)	
Yes	1,209 (58.63%)	607 (60.70%)	602 (56.69%)	(51.11%)	(51.12%)	(51.10%)	
Age (years)	38.34 (14.34)	38.28 (14.24)	38.39 (14.45)	38.03 (15.25)	37.27 (15.05)	38.75 (15.41)	
Highest education							
Primary or less	665 (32.25%)	341 (34.10%)	324 (30.51%)	(47.49%)	(47.61%)	(47.37%)	

Table 3 – continued from previous page

Variables		Unweighted	Weighted			
	Total (N=2,062)	<b>2017</b> (N=1,000)	<b>2021</b> (N=1,062)	Total	2017	2021
Secondary	1,322 (64.11%)	627 (62.70%)	695 (65.44%)	(47.84%)	(48.13%)	(47.56%)
Tertiary or higher	75 (3.64%)	32 (3.20%)	43 (4.05%)	(4.68%)	(4.27%)	(5.07%)
Currently employed						
No	756 (36.66%)	364 (36.40%)	392 (36.91%)	(37.58%)	(36.64%)	(38.46%)
Yes	1,306 (63.34%)	636 (63.60%)	670 (63.09%)	(62.42%)	(63.36%)	(61.54%)
Income quintile group						
Lowest 20%	350 (16.97%)	169 (16.90%)	181 (17.04%)	(19.98%)	(19.99%)	(19.98%)
Second 20%	367 (17.80%)	179 (17.90%)	188 (17.70%)	(19.98%)	(19.98%)	(19.99%)
Third 20%	395 (19.16%)	188 (18.80%)	207 (19.49%)	(19.91%)	(20.00%)	(19.83%)
Fourth 20%	405 (19.64%)	196 (19.60%)	209 (19.68%)	(20.10%)	(20.01%)	(20.18%)
Highest 20%	545 (26.43%)	268 (26.80%)	277 (26.08%)	(20.03%)	(20.02%)	(20.03%)
Owns a mobile phone						
No	465 (22.65%)	212 (21.31%)	253 (23.91%)	(24.79%)	(22.85%)	(26.60%)
Yes	1,588 (77.35%)	783 (78.69%)	805 (76.09%)	(75.21%)	(77.15%)	(73.40%)
Missing	9 (0.40%)	5 (0.50%)	4 (0.40%)	(0.40%)	(0.50%)	(0.30%)

Notes: Entries are n (%) or mean (standard deviation); "Used mobile phone or internet to make payments" applies only to respondents with a financial account or debit card; Statistics for the Age variable are provided as the mean (standard deviation).

Source: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

In the Formal Credit model, employment, mobile phone ownership, and survey round were found to be statistically associated with borrowing from a formal institution. Employment and mobile phone ownership were positively associated with borrowing, confirming the role of economic activity and digital access in borrowing. We found no significant relationship between income quintiles and formal credit, indicating that creditworthiness, collateral, and reliance on informal credit channels may play a larger role [106, 107]. Borrowing declined during the pandemic compared to before the pandemic by 12.5 percentage points, indicating cautious financial behavior and stricter lending standards [103].

TC 11 4 TC 4		1.1 3 6 1	T 1	T 1 '	T 1' .	· т 1 ·
Table 4. Factors	Accordated	with Main	Hinancial	Inclusion	Indicators	in Indonesia
Table 7. Factors	Associated	will wiaii	i i manciai	Inclusion	muicators	m muonesia.

Variable	Formal account		Formal saving		Formal credit	
	AME <sup>1</sup>	SE	AME <sup>1</sup>	SE	AME <sup>1</sup>	SE
Female (ref: No)						
Yes	0.076**	0.025	0.063**	0.024	-0.011	0.027
Age	0.003**	0.001	-0.003**	0.001	0.001	0.001
<b>Highest education (ref: Primary or less)</b>						
Secondary	0.161***	0.029	0.187***	0.029	-0.012	0.029
Tertiary or higher	0.394***	0.065	0.330***	0.059	0.021	0.067
Income quintile (ref: Lowest 20%)						
Second 20%	-0.013	0.040	0.118**	0.040	$-0.073^{+}$	0.042
Third 20%	0.021	0.041	$0.101^{*}$	0.039	0.025	0.042
Fourth 20%	0.018	0.041	0.163***	0.039	-0.028	0.043
Highest 20%	0.111**	0.039	0.157***	0.038	-0.056	0.041
Currently employed (ref: No)						
Yes	0.102***	0.027	0.092***	0.026	0.076**	0.029
Owns a mobile phone (ref: No)						
Yes	0.269***	0.032	0.146***	0.034	0.098**	0.034
Survey round (ref: 2017)						
2021	0.037	0.024	-0.117***	0.023	-0.125***	0.025
Observations	2,05	53	2,053		2,053	
Tjur's R <sup>2</sup>	0.15	66	0.170		0.06	9
AUC	0.73	31	0.73	8	0.65	2

 $\overline{1+p < .1; *p < .05; **p < .01; ***p < .001}$ Abbreviations: AME = Average Marginal Effect, SE = Standard Error, AUC = Area under the ROC curve. Source: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

Studies related to financial inclusion have shown nonlinear relationships between age and financial inclusion indicators [10, 24, 108]. Therefore, this study also attempted to incorporate a squared age term. The final regression results used AME as the measure of association, which does not show the squared term of age in Table 4. This is because the squared term of age was incorporated in the estimation of AMEs from the estimated logit coefficients. 10 Figure 2 presents the average predicted probabilities pertaining to the main financial inclusion indicators.

For the Formal Account model, we found a statistically significant nonlinear relationship between age and the probability of owning a formal account. Figure 2 plot (A) shows a hump-shaped pattern between age and the likelihood of owning a formal account, which peaked at 58 years of age. Valera et al. [24] found a similar pattern but with a younger peak, which ranges from 25 to 35 years of age. For Formal Credit, a more marked

<sup>10</sup> The estimated coefficients of logit regression models pertaining to main financial indicators can be found in Table A3 in the Appendix.

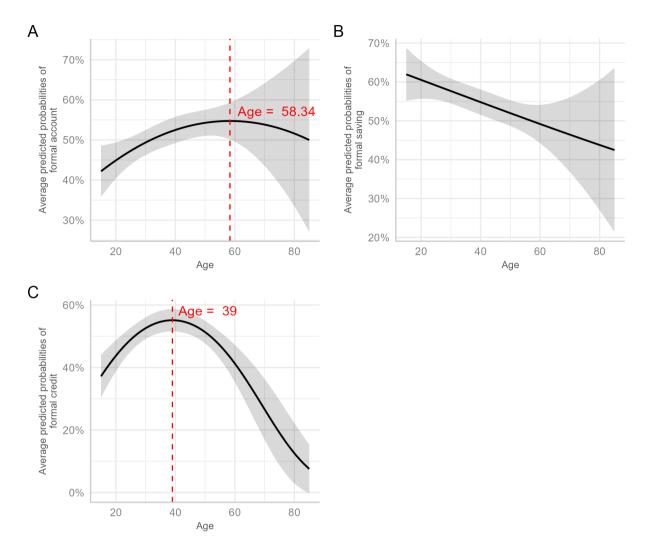


Figure 2. Average predicted probabilities of account (A), saving (B), and credit (C). *Source*: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

U-shaped relationship between age and the probability of borrowing is evident, peaking at the age of 39 years. <sup>11</sup> In contrast, Valera et al. [24] observed a peak probability of borrowing at an age range of 35-65 years. This nonlinear relationship shows that borrowing increases during productive ages but decreases in older ages, reflecting life-cycle patterns [9]. However, for Formal Savings, there is no statistically significant evidence of a nonlinear relationship with respect to the age of individuals.

Concerning gender, we found that female individuals have a higher probability of owning formal accounts and engaging in formal saving than male individuals. These disparities are inconsistent with global data. Globally, women's ownership in 2021 was four percentage points lower than men's (74% compared to 78%) [17, 109].

<sup>&</sup>lt;sup>11</sup>Note that the AME for age in the Formal Credit is not statistically significant (see Table 4), but is significant in Table A3 in the Appendix. If the AME of a variable is not statistically significant, it does not necessarily mean that the relationship between that variable is not statistically significant. Instead, it means that the probabilities are not constant across the ages. This is confirmed by the inverted u-shape line in Figure 2 plot (C).

However, there are no significant gender-based differences in formal savings [109]. Global and regional evidence suggests that women continue to face structural barriers in accessing formal financial services [110, 111]. The analysis in this study observed that women are more likely to have formal accounts (AME = 0.076) and formal savings (AME = 0.063), but are less likely to access formal credit (AME = -0.011), especially among lower-income and less-educated groups [36, 33]. However, the last relationship was not statistically significant. The lower probability of Indonesian women accessing formal credit could be explained by their stronger participation in informal credit schemes, which is often linked to lower perceived risks and community-based financial practices [112, 113, 114, 115]. However, sociocultural norms, limited income opportunities, informal employment, and gaps in financial literacy hinder broader access to formal services [116, 117, 118]. Collateral requirements and high transaction costs further exacerbate these challenges, underscoring the need for gender-sensitive financial products and targeted financial literacy programs.

Nevertheless, there are two plausible explanations for the difference in gender disparity patterns between Indonesia and other countries. First, in many Indonesian households, women are responsible for managing the day-to-day budget, allocating funds for essential needs, controlling valuable assets (e.g., jewelry or gold), and foreseeing long-term savings [119, 120, 121]. Owning a bank account is a necessity for this role. Second, many major government-to-person (G2P) social transfer programs, such as the Family Hope Program (*Program Keluarga Harapan* or PKH) and the Non-Cash Food Assistance Program (*Bantuan Pangan Non-Tunai* or BPNT), are designed to be directly transferred to the female household member. These women must have a formal bank account to receive assistance [122, 123, 124].

Aligned with previous studies [24, 69], mobile phone ownership is associated with a higher probability of owning a formal account, saving money in a formal account, and accessing formal credit. Smartphones have become the primary gateway to e-wallets, mobile banking, and digital lending, extending inclusion to underserved groups, particularly in rural areas [125, 126, 127]. This finding aligns with global evidence from the Global Findex 2021 and IMF studies [3, 128, 129] and recent findings that show that FinTech adoption contributes to narrowing incomerelated inequalities in financial services [20].

In Indonesia, high mobile penetration (85%) compared to lower active internet use (64.8%) [130] highlights the strategic importance of mobile-first FinTech solutions. Consistent with evidence from Middle East and North African (MENA) countries, where government-led cashless policies strongly correlate with socio-demographic factors and FinTech adoption [131], initiatives such as the Quick Response Code Indonesian Standard (QRIS)<sup>12</sup> and peer-to-peer (P2P) lending regulation<sup>13</sup> accelerated the shift toward digital financial platforms. The pandemic further fueled mobile-based transactions, as consumers prioritized speed, convenience, and safety [132, 133]. Fintech innovations and digital banking have leveraged this trend to serve micro, small, and medium enterprises (MSMEs) and the unbanked more effectively [134, 135]. However, the rapid expansion of FinTech lending also raises systemic risks and challenges for conventional risk management, highlighting the need for stronger consumer protection frameworks and prudential oversight [136, 137, 138].

Income and education further define the outcomes of financial inclusion. Higher income quintiles and tertiary education significantly increase the likelihood of holding formal accounts and savings, although their impact on credit is less pronounced. This finding aligns with the global evidence that income and education are consistently identified as the most important structural determinants of financial inclusion [20, 72]. This pattern suggests that financial inclusion remains skewed toward middle- and upper-income groups, while lower-income households continue to face persistent barriers, including low financial literacy, distrust of formal institutions, and limited access to digital tools [35, 139, 140]. These findings align with those of Eka [141], who highlighted that education significantly improves financial literacy and the ability to utilize formal financial services effectively. Similarly, Ansar et al. [142] argue that financial education is critical for translating access to effective and sustained use of formal financial products. Individuals with higher education are also far more likely to use mobile and Internet

<sup>&</sup>lt;sup>12</sup>Bank Indonesia Circular Letter No.21/25/DKSP of 2020 concerning implementation of QRIS.

<sup>&</sup>lt;sup>13</sup>Regulation of the Financial Services Authority No. 77/POJK.01 of 2016 concerning Information Technology-Based Money Lending Services.

banking, deepening the gap between the educated and the less educated. Addressing these divides requires tailored financial literacy programs and an affordable digital infrastructure.

Inclusive and targeted financial literacy programs are crucial for bridging access gaps, particularly among low-educated and low-income communities [143, 144, 145]. Improving financial literacy has been shown to enhance saving behavior, digital financial usage, and prudent financial decision-making, even among rural and vulnerable populations [146, 147]. Strengthening collaboration between the government, financial institutions, and technology providers is also necessary to expand the reach of financial education and digital infrastructure, ensuring that financial inclusion is more equitable and sustainable [145, 148]. This highlights that financial literacy is a critical pathway linking education and effective financial inclusion. Individuals with lower educational attainment are more likely to lack the financial knowledge and confidence needed to engage with formal financial institutions, making them vulnerable to exclusion, even when access is available [149, 150].

Age dynamics add another dimension to this issue. While age shows no significant effect on account ownership or savings, supporting the saturation hypothesis, its influence on credit is nonlinear, with borrowing peaking in productive ages and falling at older ages [151, 152]. Productive-age households are viewed as having greater repayment potential, whereas younger and older borrowers face stricter requirements. Evidence from Thailand indicates that older adults often face additional exclusion due to lower digital literacy and limited familiarity with ICT-based financial services, a challenge also relevant to Indonesia's shift to digital financial ecosystems [153]. For vulnerable groups, such as smallholder farmers or low-income households, income volatility and risks, such as climate shocks, further restrict access [154, 155]. Banks adopt conservative lending strategies and prioritize lower-risk segments to balance profitability and risk [156].

The COVID-19 pandemic exerted mixed effects; account ownership remained stable, but formal savings and credit contracts as households prioritized liquidity and reduced borrowing [102, 103]. Moreover, the COVID-19 pandemic led to a significant decline in bank credit and savings in Indonesia, primarily due to economic slowdown, heightened credit risk, and shifts in household financial behavior. Large-scale social restrictions (*Pembatasan Sosial Berskala Besar or PSBB*) and subsequent lockdown measures (*Pemberlakuan Pembatasan Kegiatan Masyarakat* or PPKM) led to business closures, reduced working hours, and widespread income losses, particularly among MSMEs and informal workers, amplifying liquidity pressures and constraining both saving and borrowing capacity [157, 158, 159]. Credit growth fell sharply as banks became more conservative amid rising non-performing loans (NPLs) and weakening credit demand from the real and household sectors, reflecting increased uncertainty and income losses [158, 159, 160, 161]. Although some households increased their precautionary savings in response to uncertainty, aggregate savings growth slowed due to widespread income reduction [161, 162].

This stability in account penetration reflects the impact of the National Strategy for Financial Inclusion (*Strategi Nasional Keuangan Inklusif or SNKI*), formalized under Presidential Regulation No. 82 of 2016, alongside initiatives such as the National Non-Cash Movement (*Gerakan Nasional Non-Tunai* or GNNT) and Branchless Financial Services for Financial Inclusion (*Layanan Keuangan Tanpa Kantor dalam Rangka Keuangan Inklusif* or *Laku Pandai*). In response to the pandemic, the government implemented several measures to stabilize the financial sector and protect vulnerable borrowers. These included the OJK's credit restructuring policy (POJK No. 11/POJK.03/2020), which aimed to ease debtor burdens and maintain banking stability [161, 163, 164], and the National Economic Recovery (*Pemulihan Ekonomi Nasional* or PEN) program, which provided fiscal stimulus, interest subsidies, and MSME credit support to sustain liquidity and purchasing power [157, 164]. Within this framework, the expansion of the People's Business Credit (*Kredit Usaha Rakyat* or KUR) scheme supported MSMEs by maintaining credit flows and mitigating default risks during lockdowns, although its distribution remained limited by risk aversion and administrative bottlenecks [164, 165].

Meanwhile, the GNNT accelerated the adoption of non-cash transactions and digital financial services across sectors, including MSMEs, enhancing transaction efficiency and financial access [166]. However, its primary impact was behavioral, encouraging digital payment habits rather than directly increasing savings or credit. The effectiveness of the GNNT and similar digitalization efforts also depends on the level of financial literacy of individuals. Individuals with lower levels of education and limited digital financial literacy often face barriers

<sup>14</sup>Regulation of the Financial Services Authority No. 19/POJK.03 of 2014 and No. 1/POJK.03 of 2022 concerning Laku Pandai.

to utilizing these services effectively, underscoring the critical role of financial education in strengthening inclusive financial resilience [149, 150].

Beyond digital and literacy barriers, sociodemographic characteristics play a decisive role in shaping financial inclusion outcomes. Differences across gender, income, education, and age continue to influence how individuals' access, use, and benefit from financial services, both before and during the pandemic. These findings demonstrate that gender, digitalization, income, education, and age jointly shape financial inclusion in Indonesia, although with varying magnitudes across accounts, savings, and credit categories. Mobile phone ownership and digital platforms remain the strongest enablers, whereas persistent gender and income gaps continue to limit equitable access to the Internet. The pandemic accelerated digital adoption while simultaneously exposing vulnerabilities in savings and borrowing behaviors. Future policies must bridge socioeconomic divides, strengthen digital ecosystems, and enhance consumer protection to ensure that the FinTech-driven inclusion remains broad-based and sustainable.

Among these factors, gender inequality deserves particular attention, as women, especially those with lower income and education, remain disproportionately excluded from formal financial systems despite increasing digital access to them. Addressing these disparities requires multilevel interventions that combine literacy, access, and policy support. Several key strategies should be prioritized to address gender disparities. First, enhancing women's financial literacy is crucial, as structured and accessible literacy programs empower women to manage finances, increase savings, and engage with formal financial systems [167, 168]. Integrated training and mentoring programs linked to access to financial products can further strengthen women's confidence and financial decision-making [169]. Second, expanding women's access to financial products, such as bank accounts, microcredit, microinsurance, and digital finance, is essential to closing the gender gap. Financial innovations tailored to women's needs and supported by mobile technology have proven effective in increasing participation, especially among low-income and rural women [170, 171, 172]. Finally, inclusive policies and institutional support are necessary to sustain progress, including affirmative programs such as productive zakat, women-focused microcredit, and MSME support schemes. Collaborative initiatives among government agencies, financial institutions, fintech providers, and women's communities can amplify outreach and foster equitable financial empowerment [173, 174].

## 3.3. Factors Associated with Use of Financial Technologies

Table 5 presents the results of the multivariable binary logistic regression for two FinTech-related outcomes: (i) payments using a mobile phone or the Internet and (ii) mobile money services. <sup>15</sup> The former was statistically significant (p < .001) and exhibited acceptable discriminatory power (AUC = 0.779). The latter model had better discriminatory power (AUC = 0.866) and was also statistically significant. For the Payment Using Mobile model, the statistically significant variables were age (and its squared term), the highest level of education, income quintile, and the survey round variable. However, for the Mobile Money Services model, the statistically significant variables were age (and its squared term), highest education, mobile phone ownership, and survey round.

Interestingly, the regression model of mobile phone/Internet payment shows that individuals in 2021 (during the pandemic) were more likely to report using mobile/Internet payments by 9.0 percentage points, showing an increased tendency to use digital payments during the pandemic, which is in line with previous studies [175, 176]. Studies have cited health concerns as one of the drivers of digital payment use [177, 178, 179]. Likewise, individuals in 2021 had a 5.6 percentage points higher probability of using mobile money services than those in 2017 (pre-pandemic). This result suggests a higher reported use of mobile money in 2021. This pattern aligns with broader evidence supporting the COVID-19 pandemic as a catalyst for digital adoption [175]. From 2020 to 2021, QRIS and e-wallet ecosystems (e.g., GoPay, OVO, Dana) became increasingly integrated into daily transactions, driven by mobility restrictions, health protocols, and a boom in e-commerce [27, 31]. However, early in the pandemic, QRIS adoption faced initial barriers, such as limited public understanding, infrastructure constraints, and resistance among micro and small merchants [180]. Nonetheless, the results show significantly higher probabilities of using mobile money services during the pandemic than before.

<sup>15</sup> See Table A4 in the Appendix for the coefficients of the logit regression.

TC 1.1 T TC .		* . 1	TT	C TO: 1	TD 1 1 '	· т 1 ·
Table 5. Factors	A scociated v	x/1fh	I ISE O	t Hinancial	Lechnologie	e in Indonesia
radic 3. ractors	1 issociated	VV I LII	030 0	i i illaliciai	recimologic	s in maonesia.

Variable	Payment us	ing mobile <sup>1</sup>	Mobile money services		
	AME <sup>2</sup>	SE	AME <sup>2</sup>	SE	
Female (ref: No)					
Yes	0.013	0.028	0.011	0.012	
Age	-0.007***	0.002	-0.003**	0.001	
<b>Highest education (ref: Primary or less)</b>					
Secondary	0.134***	0.037	0.072***	0.008	
Tertiary or higher	0.286***	0.066	0.126***	0.033	
Income quintile (ref: Lowest 20%)					
Second 20%	0.046	0.053	-0.001	0.020	
Third 20%	$0.086^{+}$	0.048	-0.006	0.018	
Fourth 20%	0.140**	0.051	0.012	0.020	
Highest 20%	0.094*	0.046	0.030	0.019	
Currently employed (ref: No)					
Yes	0.007	0.033	$0.023^{+}$	0.013	
Owns a mobile phone (ref: No)					
Yes	0.092	0.061	0.054***	0.010	
Survey round (ref: 2017)					
2021	0.090**	0.029	0.056***	0.011	
Observations	1,114		2,053		
Tjur's $R^2$	0.173		0.146		
AUC	0.779		0.866		

Results from a pooled set of 30 times imputation using Rubin's rule, using the mean for Tjur's  $R^2$  and AUC

Abbreviations: AME = Average Marginal Effect, SE = Standard Error, AUC = Area under the ROC

Source: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

In the first regression model in Table 5, education was strongly associated with payment using mobile/Internet: individuals with secondary and tertiary education have 13.4 percentage points and 28.6 percentage points higher probability of using mobile/Internet payments than those with primary education or less, reflecting the critical role of digital literacy and familiarity with Fintech [17]. Higher income quintiles are more likely to adopt mobile/Internet payments, whereas employment status and mobile phone ownership are not statistically significant factors.

In the next regression model, education was also a significant correlate, with secondary and tertiary education increasing the probability of mobile money use by approximately 7.2 percentage points and 12.6 percentage points, respectively. Income and employment status were not statistically associated with FinTech use. However, mobile phone ownership corresponds to a 5.4 percentage point higher probability of mobile money use.

Similar to the main financial indicators, studies have shown that age is a potential factor in the use of FinTech, with younger individuals being more likely to adopt FinTech products and services [181, 182]. The regression results show that age is a statistically significant correlate of FinTech in both models (Table 5). However, it is better to visually demonstrate these nonlinear relationships. Figure 3 illustrates the relationship between age and the predicted probability of using FinTech (i.e., mobile/Internet banking and mobile money services). Plot A of Figure 3 shows a strong, nonlinear relationship between age and the probability of using mobile phones or the

 $p^{2} + p < .1; *p < .05; **p < 0.01; ***p < .001.$ 

Internet to make payments; the probability is highest for the youngest individuals, then decreases sharply, but the rate of decline decreases as age increases (leveling off), dropping below 10% by approximately age 60. The confidence interval starts to show an uptick at the end of the line, which may be due to the small sample size of older persons, leading to higher uncertainty. Similarly, for Plot B of Figure 3, there is a clear negative relationship between age and the use of mobile money services; the probability starts at its peak for the youngest individuals, then decreases as age increases, and levels off at older cohorts at approximately 2%.

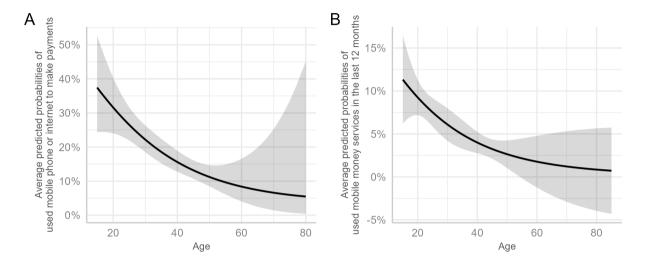


Figure 3. Average predicted probabilities of *mobintpay* (A) and *mmoney* (B). *Source*: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

Four interrelated patterns were observed when comparing the models. First, education emerges as a strong correlate, particularly for payments using mobile phones or the Internet, indicating that capability gaps beyond affordability shape FinTech usage. Higher education improves financial literacy and digital confidence, thereby increasing FinTech adoption [183, 184]. This finding aligns with those of Eka [141] and Ansar et al. [142], who underscore that education and financial literacy jointly determine access, depth, and quality of engagement with digital financial services. The key barriers to FinTech use include cost, connectivity, and the inability to understand and effectively leverage digital financial tools. Low digital and financial literacy remains a significant challenge, especially among less-educated groups [184, 185]. Furthermore, the types of Fintech services used vary by education level; individuals with higher education are more likely to engage with complex products, such as digital investments, whereas those with lower education levels predominantly rely on basic e-wallets [186].

Second, device access, as measured by mobile phone ownership, is a potential enabler but not a standalone driver of mobile money usage. While smartphone ownership significantly increases the likelihood of FinTech adoption, it must be complemented by digital literacy, trust in financial platforms, and affordable Internet access. Third, the absence of gender effects in both regression models pertaining to FinTechs contrasts with earlier findings on traditional financial inclusion (e.g., account ownership or credit), suggesting that FinTech usage may reduce gender barriers once access to devices and digital platforms is established [1]. While FinTech has the potential to bridge gender gaps, global studies show that women's FinTech adoption (21%) is still lower than men's (29%), and the gap is sometimes larger than in traditional banking [187, 188]. Fintech alone cannot eliminate these disparities without targeted interventions, such as digital literacy programs tailored to women and inclusive platform design [189, 190].

Fourth, the probability of using mobile phones/Internet to make payments and mobile money services increased in 2021 compared to 2017, indicating an upward trend in FinTech adoption and use. This pattern has also been observed in other countries [57, 177, 191, 192, 193, 194, 195]. In Indonesia, the context of early QRIS implementation from 2020 to 2021 is crucial in understanding the background of this increase. Although there

were adoption barriers at the onset of the pandemic, such as limited public awareness, infrastructure constraints, and initial reluctance among small and micro-businesses [180], the pandemic catalyzed a shift toward digital financial services, particularly through e-commerce growth and the adoption of contactless transactions [27].

These results underscore that education, digital literacy, and access to devices are the most crucial drivers of FinTech adoption. Gender divides are less pronounced once basic access barriers are removed from the equation. Policy initiatives, such as the Payment System Blueprint 2025 and the 2025-2029 National Medium-Term Plan (*Rencana Pembangunan Jangka Menengah Nasional* or RPJMN), combined with private sector partnerships for digital literacy campaigns, are key to expanding inclusive FinTech ecosystems in Indonesia. Studies have shown that the government's role in actively promoting digital payments is also key to their increased use [196, 197].

## 3.4. Sensitivity Analyses

Given that the Global Findex public microdata sets only provide sampling weights but do not include identifiers for PSU and strata, we specified the survey design as independent (i.e., set ids = 1 in "svydesign" function). This approach simplified the sampling design of the Global Findex survey [86, 87]. Although population weights were incorporated in the estimation of regression coefficients and AME, the variance (standard error) was derived under the assumption of independent observations. We conducted three sensitivity analyses to ensure the robustness of our results. First, we fitted weighted logistic regression models using the "glm" function and computed robust standard errors for inference. Second, we adjusted the variance estimates of the main models using the reported design effect (Deff) to partially account for the complex survey design. Third, we re-estimated the models using a probit link function (probit regression). This analysis serves as a robustness check to ensure that our findings are not dependent on the model's specific distributional assumption. While the logit regression model assumes that the error term follows a standard logistic distribution, the probit regression model assumes that the error term follows a standard normal distribution (Greene, 2012). By estimating both, we can confirm that our results are robust to the choice of link function. Moreover, we adjusted the variance estimates using the reported Deff. All robustness checks yielded similar AME estimates (see Figures A1 and A2 in the Appendix), suggesting that our results are largely consistent when applying sample weights and using an alternative link function (probit).

## 4. Conclusion

This study examined the determinants of financial inclusion and FinTech usage in Indonesia, focusing on the periods before and during the COVID-19 pandemic, using the 2017 and 2021 rounds of the Global Findex database. The findings reveal a nuanced landscape of the topic. Formal account ownership has reached a near-saturation point, showing little change between 2017 and 2021. In contrast, formal savings and borrowing declined during the pandemic due to income shocks, increased financial uncertainty, and the prioritization of short-term liquidity. Meanwhile, there is evidence that digital payment and FinTech adoption were higher in 2021 than in 2017, consistent with broader evidence suggesting that the pandemic accelerated the digitalization of financial services.

The results confirm that structural and demographic factors strongly influence the likelihood of traditional and digital financial inclusion. Education emerges as a strong correlate, as higher educational attainment substantially increases the likelihood of owning a formal account, saving, borrowing, and using digital payment channels (DPCs). Income disparities remain pronounced, with middle- and upper-income groups disproportionately benefiting from both traditional and digital financial services, leaving lower-income households underserved. Mobile phone ownership is a significant potential enabler of financial inclusion, as it substantially increases the likelihood of accessing formal accounts, saving, and engaging in digital transactions. However, device ownership alone is insufficient without complementary digital and financial literacy skills. Gender disparities also persist: while women are more likely to have formal accounts and maintain formal savings, they have a lower probability of accessing formal credit. These patterns highlight the enduring sociocultural and structural constraints that must be addressed to achieve equitable financial inclusion.

Indonesia's financial inclusion strategy must evolve beyond its traditional focus on account access to promote meaningful usage and quality engagement with financial services, thereby addressing the gaps in financial literacy. Efforts should focus on increasing formal savings, expanding access to microcredit, and promoting long-term financial planning, particularly through inclusive digital channels tailored to marginalized groups, such as women, informal workers, and rural households. Strengthening financial and digital literacy is critical. As education is a strong correlate of both traditional and digital financial inclusion indicators, nationwide initiatives should be integrated into school curricula, vocational training, and MSME development programs to ensure that all segments of society understand and effectively utilize FinTech.

This study's results also suggest that there are gender-related disparities in formal account ownership and formal savings. Therefore, we propose several methods to address these disparities. First, we must promote a model of shared financial partnership and responsibility within the family by encouraging men to take a more active role in managing the family's daily finances. Second, further studies should be conducted to understand the reasons behind these gaps. This can be achieved using qualitative methods. Third, financial authorities, such as the Financial Services Authority (Otoritas Jasa Keuangan or OJK) and Bank Indonesia (Central Bank of the Republic of Indonesia), should mandate that all financial institutions collect, analyze, and report sex-disaggregated data on all financial products and digital transactions. Together with qualitative data, these quantitative data would enable evidence-based decision-making to curb gender-related disparities in financial inclusion.

Improving digital infrastructure is another essential priority. Bridging the urban-rural divide requires the expansion of affordable Internet connectivity, the acceleration of 4G/5G deployment, and a reduction in broadband costs. Public-private collaboration, including shared QRIS infrastructure and interoperable payment ecosystems, can be pivotal in ensuring widespread and equitable access to digital financial services. Similarly, addressing gender disparities requires gender-responsive financial systems that provide flexible collateral requirements, community-based savings programs, and female-focused digital literacy campaigns to overcome structural and socio-cultural barriers.

Balancing innovation and financial stability is also critical. The rapid growth of FinTech lending and peer-to-peer platforms necessitates the development of adaptive regulatory frameworks to prevent systemic risks and protect consumers. Policies must prioritize responsible digital finance by emphasizing data privacy, transparent pricing, robust credit scoring, and real-time monitoring. Finally, policymakers must capitalize on the digital momentum that the pandemic catalyzed. Scaling QRIS and e-wallet adoption, promoting e-commerce integration, and ensuring platform interoperability can help maintain the trajectory of digital inclusion in the Philippines. Simultaneously, continuous monitoring of user behavior will allow for the early identification of gaps in underserved segments.

Although this study provides a comprehensive assessment of financial inclusion and FinTech adoption in Indonesia using Global Findex data, several areas warrant further investigation. First, future research could employ micro-level panel data to examine the long-term effects of financial inclusion on household resilience, poverty reduction, and entrepreneurship, particularly in a post-pandemic context. Second, qualitative studies focusing on behavioral and cultural factors, such as trust in financial institutions, digital literacy gaps, and gender norms, would enrich our understanding of barriers to inclusion beyond socioeconomic variables. Third, future studies should investigate the interplay between FinTech adoption and financial stability, particularly the risks associated with the rapid growth of peer-to-peer (P2P) lending and digital credits. Finally, as digital payment ecosystems (e.g., QRIS and e-wallets) continue to evolve, research integrating transaction-level data from financial service providers and regulators would provide deeper insights into usage trends, consumer protection issues, and the impact of emerging technologies, such as open banking and artificial intelligence (AI)-driven credit scoring.

## Acknowledgement

We thank the World Bank for providing access to the Findex datasets (https://www.worldbank.org/en/publication/globalfindex/Data). This study did not receive any funding. Grammarly and Paperpal were used to correct grammatical errors and improve the flow of the manuscript. The authors declare that there

are no potential conflicts of interest related to this work's research, writing, or publication. The authors have made equal contributions to this paper.

## Availability of data and materials

The raw data sets are publicly available to download from https://www.worldbank.org/en/publication/globalfindex/Data. The data and R scripts used for the analyses can be found here: https://drive.google.com/drive/folders/lqlIkBOohvHj-xNnPJEgXYM-oKxFX5LF1? usp=drive\_link.

# Appendix Percentages of missing values in the fourth dependent variable ("mobintpay")

Table A1. Distribution of "mobintpay" by the survey year.

	Unweighted				Weighted		
Variable	Total	2017	2021	Total	2017	2021	
	N = 1,114	N = 535	N = 579	N = 1,038	N = 491	N = 548	
Used mobile phone or internet to make payments							
No	748	353	395	676	321	355	
	(78.82%)	(82.28%)	(75.96%)	(78.16%)	(83.04%)	(74.22%)	
Yes	201	76	125	189	66	123	
	(21.18%)	(17.72%)	(24.04%)	(21.84%)	(16.96%)	(25.78%)	
Missing							
	165	106	59	174	104	70	
	(15%)	(20%)	(10%)	(17%)	(21%)	(13%)	

*Notes*: N represents the number of observations for each category; percentages in parentheses are row percentages. *Source*: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

## Factors associated with missing values in the fourth dependent variable ("mobintpay")

Table A2. Logistic regression results of missing values for the fourth dependent variable (mobintpay).

Variable	2017	7	202	1
	Coef <sup>1</sup>	SE	Coef <sup>1</sup>	SE
Individual is a female				
No		_	_	_
Yes	0.254	0.248	-0.188	0.309
Age (years)	-0.021	0.043	-0.071	0.050
Age (years), squared	0.000	0.001	0.001	0.001
Highest education				
Primary or less	_	_	_	_
Secondary	-0.729**	0.265	-0.483	0.375
Tertiary or higher	-16.607	742	-1.368	1.09
Income quintile group				
Lowest 20%	_		_	_
Second 20%	0.253	0.413	0.441	0.389
Third 20%	-0.190	0.414	-1.004*	0.486
Fourth 20%	-0.068	0.404	-0.703	0.453
Highest 20%	-0.310	0.388	-1.435**	0.517
Currently employed				
No	_		_	
Yes	-0.260	0.244	-0.411	0.314
Owns a mobile phone				
No	_		_	_
Yes	-0.022	0.390	-1.014*	0.395
No. Obs.	535		579	

 $<sup>^{1}</sup>$  \*p < .05; \*\*p < .01; \*\*\*p < .001.

*Notes*: Coef = Logistic regression coefficient (log-odds); SE = Standard Error. *Source*: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

## Coefficients of logit regression model of main financial inclusion indicators

Table A3. Logit regression estimations of factors associated with main financial inclusion indicators.

Variable	Formal account		Formal saving		Formal credit	
	Coef <sup>1</sup>	SE	Coef <sup>1</sup>	SE	Coef <sup>1</sup>	SE
Intercept	-2.933	0.457	-0.859 +	0.445	-1.876 ***	0.433
Female (ref: No)						
Yes	0.360 ***	0.121	$0.308\ ^*$	0.120	-0.048	0.114
Age	0.037 +	0.022	-0.014	0.022	0.103 ***	0.022
Age squared	-0.0003	0.000	0.000	0.000	-0.001 ***	0.000
<b>Highest education (ref: Primary or less)</b>						
Secondary	0.715 ***	0.129	0.840 ***	0.128	-0.052	0.126
Tertiary or higher	1.950 ***	0.424	1.609 ***	0.351	0.091	0.290
Income quintile (ref: Lowest 20%)						
Second 20%	-0.058	0.187	$0.553^{***}$	0.187	-0.313 +	0.181
Third 20%	0.097	0.188	0.472 *	0.185	0.107	0.180
Fourth 20%	0.085	0.190	0.769 ***	0.186	-0.119	0.183
Highest 20%	0.520 ***	0.181	0.743 ***	0.181	-0.242	0.176
Currently employed (ref: No)						
Yes	$0.477^{***}$	0.128	0.443 ***	0.127	0.324 ***	0.124
Owns a mobile phone (ref: No)						
Yes	1.230 ***	0.155	0.675 ***	0.152	0.422 ***	0.149
Survey round (ref: 2017)						
2021	0.173	0.113	-0.565 ***	0.115	-0.530 ***	0.108
Observations	2053		2053		2053	
Tjur's R2	0.156		0.170		0.069	
AUC	0.731		0.738		0.652	

 $<sup>^{1}\ ^{+}</sup>p<.1;\ ^{*}p<.05\ ^{**}p<.01;\ ^{***}p<.001.$ 

*Notes*: Coef = Logistic regression coefficient (log-odds); SE = Standard Error; AUC = Area Under the ROC Curve. *Source*: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

## Coefficients of logit regression models of use of financial technologies

Table A4. Logit regression estimations of factors associated with use of financial technologies.

Variable	Payment using mobile		Mobile money services		
	Coef <sup>1</sup>	SE	Coef <sup>1</sup>	SE	
Intercept	-2.187	1.435	-6.388 **	2.018	
Female (ref: No)					
Yes	0.097	0.207	0.212	0.242	
Age	-0.073	0.063	-0.060	0.090	
Age squared	0.0003	0.001	0.0001	0.001	
<b>Highest education (ref: Primary or less)</b>					
Secondary	1.143 **	0.406	2.731 ***	0.595	
Tertiary or higher	$1.971^{***}$	0.475	3.388 ***	0.654	
Income quintile (ref: Lowest 20%)					
Second 20%	0.414	0.480	-0.014	0.459	
Third 20%	$0.720^{+}$	0.433	-0.153	0.428	
Fourth 20%	1.069 *	0.427	0.254	0.413	
Highest 20%	0.773 <sup>+</sup>	0.415	0.558	0.391	
Currently employed (ref: No)					
Yes	0.050	0.238	0.479 <sup>+</sup>	0.290	
Owns a mobile phone (ref: No)					
Yes	0.791	0.631	$1.867^{**}$	0.673	
Survey round (ref: 2017)					
2021	0.649 **	0.212	1.168 ***	0.240	
Observations	111	4	2053		
Tjur's R2	0.17	73	0.146		
AUC	0.77	19	0.866		

 $<sup>^{1}\ ^{+}</sup>p<0.1;\ ^{*}p<0.05;\ ^{**}p<0.01;\ ^{***}p<0.001.$ 

*Notes*: Coef = Logistic regression coefficient (log-odds); SE = Standard Error; AUC = Area Under the ROC Curve. *Source:* Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

## Sensitivity analyses of main financial inclusion models

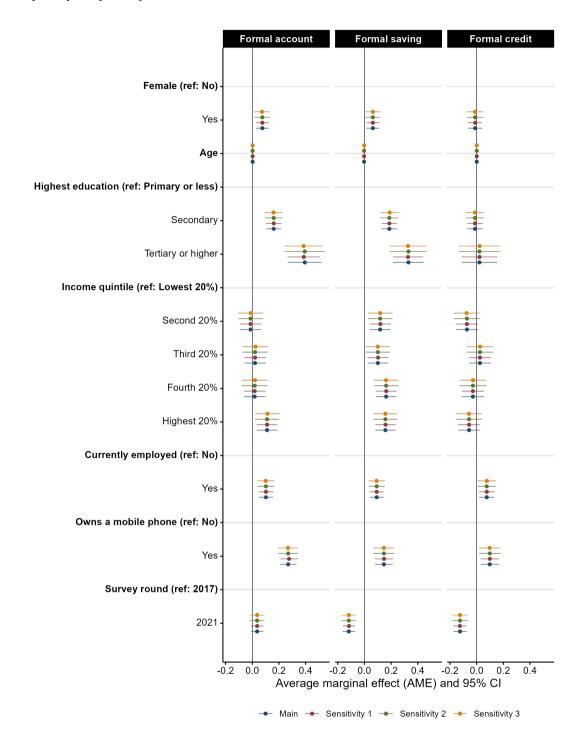


Figure A1. Results of sensitivity analyses of the main financial inclusion indicators.

## Sensitivity analyses of the use of financial technology models

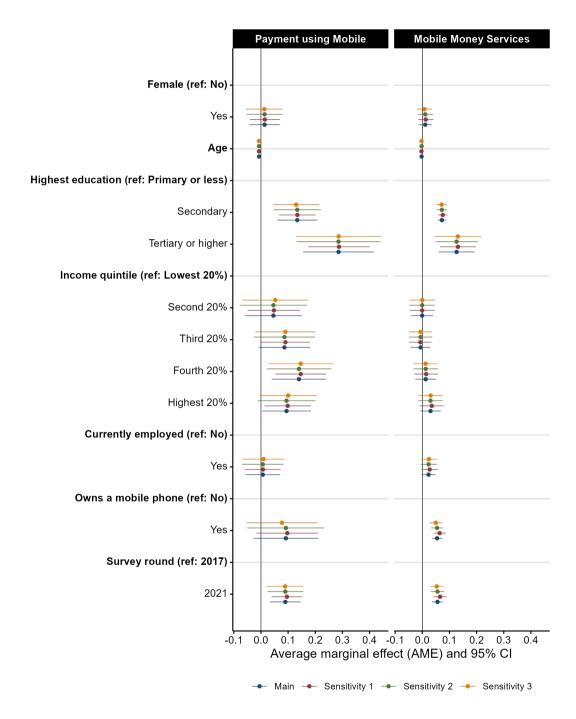


Figure A2. Results of sensitivity analyses of the use of financial technologies.

#### REFERENCES

- 1. L. Cabeza-García, E. B. Del Brio, and M. L. Oscanoa-Victorio, Female financial inclusion and its impacts on inclusive economic development, Women's Studies International Forum, vol. 77, p. 102300, 2019.
- 2. B. M. Mulili, Financial inclusion as a tool for women's economic empowerment in Africa: Achieving UN's 2030 SDG, in Empowering African women for sustainable development: Toward achieving the United Nations' 2030 Goals, edited by O. Adeola, Palgrave Macmillan, London, pp. 133-144, 2020.
- 3. A. Demirgüç-Kunt, L. Klapper, D. Singer, S. Ansar, and J. Hess, The Global Findex Database 2017: Measuring Financial Inclusion and Opportunities to Expand Access to and Use of Financial Services, The World Bank Economic Review, vol. 34, no. Suppl. 1, pp. 86-107, 2020.
- 4. X. Song, J. Li, and X. Wu, Financial inclusion, education, and employment: Empirical evidence from 101 countries, Humanities and Social Sciences Communications, vol. 11, no. 1, p. 172, 2024.
- 5. R. Gutiérrez-Romero and M. Ahamed, COVID-19 response needs to broaden financial inclusion to curb the rise in poverty, World Development, vol. 138, p. 105229, 2021.
- S.S. Kumar and Q. Jie, Exploring the role of financial inclusion in poverty reduction: An empirical study, World Development Sustainability, vol. 3, p. 100103, 2023.
- T. Suri, *Mobile money*, Annual Review of Economics, vol. 9, pp. 497–520, 2017.
- T. Liu, M. Fan, Y. Li, and P. Yue, Financial literacy and household financial resilience, Finance Research Letters, vol. 63, p. 105378, 2024
- 9. D. M. Turégano and A. G. Herrero, Financial inclusion, rather than size, is the key to tackling income inequality, The Singapore Economic Review, vol. 63, no. 1, pp. 167-184, 2018.
- 10. F. Allen, A. Demirguc-Kunt, L. Klapper, and M. S. Martinez Peria, The foundations of financial inclusion: Understanding ownership and use of formal accounts, Journal of Financial Intermediation, vol. 27, pp. 1-30, 2016.
- W. Chinnakum, Impacts of financial inclusion on poverty and income inequality in developing Asia, The Singapore Economic Review, vol. 68, no. 04, pp. 1375-1391, 2023.
- 12. S. A. Churchill and V. B. Marisetty, Financial inclusion and poverty: A tale of forty-five thousand households, Applied Economics, vol. 52, no. 16, pp. 1777-1788, 2020.
- 13. M. A. Omar and K. Inaba, Does financial inclusion reduce poverty and income inequality in developing countries? A panel data analysis, Journal of Economic Structures, vol. 9, no. 1, p. 37, 2020.
- 14. P. Choudhary, C. Ghosh, and M. Thenmozhi, Impact of fintech and financial inclusion on sustainable development goals: Evidence from cross country analysis, Finance Research Letters, vol. 72, p. 106573, 2025.
- 15. UNSGSA, Financial inclusion: Technology, innovation, progress. United Nations Secretary General's Special Advocate for Inclusive Finance for Development (UNSGSA), 2018.
- 16. S. Yap, H. S. Lee, and P. X. Liew, The role of financial inclusion in achieving finance-related sustainable development goals (SDGs): A cross-country analysis, Economic Research-Ekonomska Istraživanja, vol. 36, no. 3, p. 2212028, 2023.
- 17. A. Demirgüç-Kunt, L. Klapper, D. Singer, and S. Ansar, The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19. World Bank, 2022
- 18. N. Kshetri, The role of artificial intelligence in promoting financial inclusion in developing countries, Journal of Global Information Technology Management, vol. 24, no. 1, pp. 1-6, 2021.
- 19. A. Demir, V. Pesqué-Cela, Y. Altunbas, and V. Murinde, Fintech, financial inclusion and income inequality: A quantile regression approach, The European Journal of Finance, vol. 28, no. 1, pp. 86–107, 2022.
- 20. B. B. Ashenafi and Y. Dong, Financial Inclusion, fintech, and income inequality in Africa, FinTech, vol. 1, no. 4, pp. 376–387, 2022.
- 21. P. Khera, S. Ng, S. Ogawa, and R. Sahay, Measuring digital financial inclusion in emerging market and developing economies: A new index, Asian Economic Policy Review, vol. 17, no. 2, pp. 213-230, 2022.
- 22. L.-Y. Tay, H.-T. Tai, and G.-S. Tan, Digital financial inclusion: A gateway to sustainable development, Heliyon, vol. 8, no. 6, p. e09766, 2022.
- 23. Bappenas RI, Indonesia's Voluntary National Review 2021. Sustainable and resilient recovery from the COVID-19 pandemic for the achievement of the 2030 agenda, National Development Planning Agency (Badan Perencanaan Pembangunan Nasional Republik Indonesia - Bappenas RI), 2021.
- 24. M. L. G. Valera, Z. Lei, and J. H. Fong, Determinants of financial inclusion in Southeast Asia, Applied Economics, vol. 57, no. 20, pp. 2533-2550, 2025.
- V. Haldane, C. De Foo, S. M. Abdalla, A.-S. Jung, M. Tan, S. Wu, A. Chua, M. Verma, P. Shrestha, S. Singh, T. Perez, S. M. Tan, M. Bartos, S. Mabuchi, M. Bonk, C. McNab, G. K. Werner, R. Panjabi, A. Nordström, and H. Legido-Quigley, Health systems resilience in managing the COVID-19 pandemic: Lessons from 28 countries, Nature Medicine, vol. 27, no. 6, pp. 964-980, 2017.
- 26. S. Naseer, S. Khalid, S. Parveen, K. Abbass, H. Song, and M. V. Achim, COVID-19 outbreak: Impact on global economy, Frontiers of Public Health, vol. 10, pp. 1009393, 2023.
- 27. S. Ahmed and S. Sur, Change in the uses pattern of digital banking services by Indian rural MSMEs during demonetization and Covid-19 pandemic-related restrictions, VILAKSHAN-XIMB Journal of Management, vol. 20, no. 1, pp. 166-192, 2023.
- 28. O. Saka, B. Eichengreen, and C. G. Aksoy, Epidemic exposure, financial technology, and the digital divide, Journal of Money,
- Credit and Banking, vol. 54, no. 7, pp. 1913–1940, 2022.

  29. N. D. Sarto and P. K. Ozili, FinTech and financial inclusion in emerging markets: A bibliometric analysis and future research agenda, International Journal of Emerging Markets, vol. 20, no. 13, pp. 270-290, 2025.
- 30. R. J. Nathan, B. Setiawan, and M. N. Quynh, Fintech and financial health in Vietnam during the COVID-19 pandemic: In-depth descriptive analysis, Journal of Risk and Financial Management, vol. 15, no. 3, p. 125, 2022.
- 31. L. Oanh Ha, V. C. Nguyen, and T. Hieu Nguyen, Developing financial inclusion in the context of Covid-19 pandemic: The case of a developing country, in Computer intelligence against pandemics: Tools and methods to face new strains of COVID-19, edited by S. Bhattacharyya, J. S. Banerjee, S. Gorbachev, K. Muhammad, and M. Koeppen, De Gruyter, New York, pp. 173–186, 2023.

- 32. World Bank, Global financial development report 2014: Financial inclusion. World Bank, Washington, D.C., 2021.
- 33. A. Nugroho and E. Y. Purwanti, *Determinan inklusi keuangan di Indonesia (Global Findex 2014*, Jurnal Dinamika Ekonomi Pembangunan, vol. 1, no. 1, pp. 1–13, 2018.
- 34. E. Susilowati and L. Leonnard, Factors influence financial inclusion: Evidence from Indonesian micro data, Etikonomi, vol. 18, no. 1, pp. 121–132, 2019.
- 35. I. Susilowati, M. K. Fikri, D. M. Sari, A. Razak, U. Khasanah, M. A. Djatayu, and I. Suciati, *Exploring determinants of Indonesia's financial inclusion level: Based on 2017 Global Findex data*, Jurnal Ekonomi Dan Bisnis, vol. 27, no. 1, pp. 249–270, 2024.
- 36. M. A. Esquivias, N. Sethi, M. D. Ramandha, and A. D. Jayanti, Financial inclusion dynamics in Southeast Asia: An empirical investigation on three countries, Business Strategy & Development, vol. 4, no. 2, pp. 203–215, 2021.
- 37. N. Khusniati and M. G. Yusuf, From phone to finance: Indonesian female patterns in store payments, Journal of Scientific Research, Education, and Technology (JSRET), vol. 4, no. 2, pp. 1118–1136, 2025.
- 38. R. Shrestha and S. Nursamsu, *Financial inclusion and savings in Indonesia*, in Handbook of Mathematical Models in Computer Vision, edited by T. Cavoli and R. Shrestha, Routledge, Abingdon, Oxfordshire, pp. 227–250, 2021.
- 39. V. Y. Putri and I. Nurhayati, *Does financial inclusion improve financial literacy? An ASEAN cross-country analysis*, The 6th International Conference on Vocational Education, Applied Science and Technology (ICVEAST 2023), 2023.
- 40. O. Dluhopolskyi, O. Pakhnenko, S. Lyeonov, A. Semenog, N. Artyukhova, M. Cholewa-Wiktor, and W. Jastrzębski, *Digital financial inclusion: COVID-19 impacts and opportunities*, Sustainability, vol. 15, no. 3, p. 2383, 2023.
- 41. F. Mabrouk, J. Bousril, M. Elhaj, J. Binsuwadan, and H. Alofaysan, *Empowering women through digital financial inclusion: Comparative study before and after COVID-19*, Sustainability, vol. 15, no. 12, p. 9154, 2023.
- 42. R. Djalante, J. Lassa, D. Setiamarga, A. Sudjatma, M. Indrawan, B. Haryanto, C. Mahfud, M. S. Sinapoy, S. Djalante, I. Rafliana, L. A. Gunawan, G. A. K. Surtiari, and H. Warsilah, *Review and analysis of current responses to COVID-19 in Indonesia: Period of January to March 2020*, Progress in Disaster Science, vol. 6, pp. 100091, 2020.
- 43. Government of Indonesia, Peraturan Pemerintah Nomor 21 Tahun 2020 tentang Pembatasan Sosial Berskala Besar dalam Rangka Percepatan Penanganan Corona Virus Disease 2019 [Government Regulation Number 21 of 2020 concerning Large-Scale Social Restrictions in the Context to Accelerate the Mitigation of Corona Virus Disease 2019], Government of Indonesia, Jakarta, 2020.
- 44. C. V. Septianurmayanti and A. D. Prasetyo, *Practical signal recovery from random projections*, Proceedings of the 3rd Annual Management, Business and Economics Conference (AMBEC 2021), 2022.
- 45. G. Marin and R. J. Palacios, The role of digital in the COVID-19 social assistance response. World Bank Group. http://documents.worldbank.org/curated/en/099830009302217091. The World Bank, Washington, D.C., 2022.
- 46. H. Palaon, Digitising the social safety net: Lessons from Indonesia., Lowy Institute, Sydney, 2024.
- 47. R. Wahyudi, F. Sondakh, and V. N. A. R. Permatasari, Social protection inclusion in Indonesia's remote areas: Identifying and addressing gaps and challenges. https://documentsl.worldbank.org/curated/en/099062624071020814/pdf/P177341-b77c6fc9-f2db-4e5c-b24f-c41e1ce945ca.pdf, The World Bank, Washington, D.C., 2024.
- 48. World Bank, Global Financial Inclusion (Global Findex) Database 2017 [dataset]. https://doi.org/10.48529/FKZS-AT21. Development Data Group, World Bank, Washington, D.C., 2018.
- 49. World Bank, Global Financial Inclusion (Global Findex) Database 2021 [dataset]. https://doi.org/10.48529/ JQ97-AJ70. Development Data Group, World Bank, Washington, D.C., 2022.
- P. K. Ozili, *Theories of financial inclusion*, in Uncertainty and challenges in contemporary economic behaviour, edited by E. Özen and S. Grima, Emerald Publishing Limited, Leeds, pp. 89–115, 2020.
- 51. P. K. Ozili, *Vulnerable group theory of financial inclusion*, Perspectives on global development and technology, vol. 22, no. 5-6, pp. 396–414, 2024.
- 52. P.K. Ozili, Effect of gender equality on financial stability and financial inclusion, Social Responsibility Journal, vol. 20, no. 2, pp. 205-223, 2024.
- 53. F. D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Quarterly, vol. 13, no. 3, pp. 319–340, 1989.
- 54. M. N. Bailusy, J. Pollack, J. Fahri, D. Amarullah, and I. Buamonabot, *Determinants of Indonesian SMEs' intentions to adopt fintech: An innovation diffusion theory perspective*, Journal of Indonesian Economy and Business, vol. 40, no. 2, pp. 196–213, 2025.
- 55. S. Modgil, Y. K. Dwivedi, N. P. Rana, S. Gupta, and S. Kamble, *Has Covid-19 accelerated opportunities for digital entrepreneurship?*An Indian perspective, Technological Forecasting and Social Change, vol. 175, pp. 121415, 2022.
- 56. J. Fu and M. Mishra, Fintech in the time of COVID19 Technological adoption during crises, Journal of Financial Intermediation, vol. 50, p. 100945, 2022.
- 57. D. Tut, FinTech and the COVID-19 pandemic: Evidence from electronic payment systems, Emerging Markets Review, vol. 54, p. 100999, 2023.
- 58. E. M. Rogers, Diffusion of innovations (3rd ed.), The Free Press, New York, 1983.
- 59. A. Demirgüç-Kunt, L. Klapper, D. Singer, S. Ansar, and J. Hess, *The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution*. World Bank, 2018.
- 60. E. Aracil, J. Jung, and A. Melguizo, Leveraging fintech mobile money to expand banks' financial services in developing countries, Finance Research Letters, vol. 72, p. 106280, 2025.
- 61. R. J. Cull, T. D. Ehrbeck, and N.-A. Holle, Financial inclusion and development: Recent impact evidence. http://documents.worldbank.org/curated/en/269601468153288448, World Bank Group, Washington, D.C., 2014.
- 62. M. Sarma and J. Pais, *Financial inclusion and development*, Journal of International Development, vol. 23, no. 5, pp. 613–628, 2011.
- 63. P. Gomber, J.-A. Koch, and M. Siering, *Digital finance and FinTech: Current research and future research directions* Journal of Business Economics, vol. 87, no. 5, pp. 537–580, 2017.
- 64. P. K. Ozili, Impact of digital finance on financial inclusion and stability, Borsa Istanbul Review, vol. 18, no. 4, pp. 329–340, 2018.
- 65. A. Agarwal and V. A. Assenova, *Mobile Money as a Stepping Stone to Financial Inclusion: How Digital Multisided Platforms Fill Institutional Voids*, Organization Science, vol. 35, no. 3, pp. 769–787, 2024.

- 66. W. Jack and T. Suri, Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution, American Economic Review, vol. 104, no. 1, pp. 183–223, 2014.
- 67. World Bank, Global Findex 2021: Microdata codebook, World Bank, Washington, D.C., 2018.
- 68. K. F. Akeju, *Household financial behaviour: The role of financial inclusion instruments in Nigeria*, Journal of Sustainable Finance & Investment, pp. 1–13, 2022.
- 69. J. Ali and A. K. Ghildiyal, Socio-economic characteristics, mobile phone ownership and banking behaviour of individuals as determinants of digital financial inclusion in India, International Journal of Social Economics, vol. 50, no. 10, pp. 1375–1392, 2023.
- 70. H. Baber, Financial inclusion and FinTech: A comparative study of countries following Islamic finance and conventional finance, Qualitative Research in Financial Markets, vol. 12, no. 1, pp. 24–42, 2019.
- 71. T. Petrikova, Digital payments as an indicator of financial inclusion in Euro Area countries. *E&M Economics and Management*, vol. 27, no. 2, pp. 162–182, 2024.
- 72. A. Zins and L. Weill, *The determinants of financial inclusion in Africa*, Review of Development Finance, vol. 6, no. 1, pp. 46–57, 2016.
- 73. W. D. Bekele, *Determinants of financial inclusion: A comparative study of Kenya and Ethiopia*, Journal of African Business, vol. 24, no. 2, pp. 301–319, 2023.
- 74. J. Fox and S. Weisberg. An R companion to applied regression (3rd ed.). SAGE Publications Inc., Thousand Oaks, 2019.
- 75. J. S. Long and J. Freese, Regression Models for Categorical Dependent Variables in Stata, Stata Press, College Station, Texas, 2014.
- 76. J. A. Gallis and E. L. Turner, *The risks of odds ratios*, BJOG: An International Journal of Obstetrics & Gynaecology, vol. 126, no. 13, pp. 1556–1557, 2019.
- 77. M. J. Knol, R. G. Duijnhoven, D. E. Grobbee, K. G. M. Moons, and R. H. H. Groenwold, *Potential misinterpretation of treatment effects due to use of odds ratios and logistic regression in randomized controlled trials*, PLOS ONE, vol. 6, no. 6, pp. e21248, 2011.
- 78. P. Ranganathan, R. Aggarwal, and C. S. Pramesh, *Common pitfalls in statistical analysis: Odds versus risk*, Perspectives in Clinical Research, vol. 6, no. 4, pp. 222–224, 2015.
- 79. K. L. Sainani, Understanding Odds Ratios, PM&R, vol. 3, no. 3, pp. 263–267, 2011.
- 80. S. Greenland, J. M. Robins, and J. Pearl, *Confounding and collapsibility in causal inference*, Statistical Science, vol. 14, no. 1, pp. 29–46, 1999.
- 81. S. Greenland, *Noncollapsibility, confounding, and sparse-data bias. Part 1: The oddities of odds*, Journal of Clinical Epidemiology, vol. 138, pp. 178–181, 2021.
- 82. K. B. Karlson and B. Jann, Marginal odds ratios: What they are, how to compute them, and why sociologists might want to use them, Sociological Science, vol. 10, pp. 332–347, 2023.
- 83. R Core Team, R: A language and environment for statistical computing, R Foundation for Statistical Computing, 2025.
- 84. T. Lumley, Analysis of complex survey samples, Journal of Statistical Software, vol. 9, pp. 1-19, 2004.
- 85. T. Lumley, survey: Analysis of complex survey samples [computer software], R Foundation for Statistical Computing, 2025.
- 86. World Bank, Global Findex 2017: Survey methodology, World Bank, Washington, D.C., 2018.
- 87. World Bank, Global Findex 2021: Survey methodology. https://thedocs.worldbank.org/en/doc/f3ee545aac6879c27f8acb61abc4b6f8-0050062022/original/Findex-2021-Methodology.pdf, World Bank, Washington, D.C., 2018.
- 88. S. Van Buuren, Flexible Imputation of Missing Data (2nd Ed.), CRC Press, Boca Raton, 2018.
- 89. D. B. Rubin, Multiple imputation for nonresponse in surveys, John Wiley & Sons, Inc., Hoboken, N.J., 1987.
- 90. D. B. Rubin, *Multiple imputation after 18+ years*, Journal of the American Statistical Association, vol. 91, no. 434, pp. 473–489, 1996.
- 91. S. van Buuren and K. Groothuis-Oudshoorn, *Multivariate Imputation by Chained Equations in R*, Journal of Statistical Software, vol. 45, no. 3, pp. 1–67, 2011.
- 92. T. Lumley, mitools: Tools for Multiple Imputation of Missing Data. R package version 2.4, https://CRAN.R-project.org/package=mitools, 2019.
- 93. V. Arel-Bundock, N. Greifer, and A. Heiss, *How to Interpret Statistical Models Using marginal effects for R and Python*, Journal of Statistical Software, vol. 111, no. 9, pp. 1–32, 2024.
- 94. D. Lüdecke, M. S. Ben-Shachar, I. Patil, P. Waggoner, and D. Makowski, performance: An R package for assessment, comparison and testing of statistical models, Journal of Open Source Software, vol. 6, no. 60, p. 3139, 2021.
- 95. T. Tjur, Coefficients of determination in logistic regression models—a new proposal: The coefficient of discrimination, The American Statistician, vol. 63, no. 4, pp. 366–372, 2009.
- 96. T. D. Hocking, Weighted ROC: Fast, weighted ROC curves [computer software], https://cran.r-project.org/web/packages/WeightedROC/index.html, 2020.
- 97. J. Fox and G. Monette, *Generalized collinearity diagnostics*, Journal of the American Statistical Association, vol. 87, no. 417, pp. 178–183, 1992.
- 98. J. Fox, S. Weisberg, B. Price, D. Adler, D. Bates, G. Baud-Bovy, B. Bolker, S. Ellison, D. Firth, M. Friendly, G. Gorjanc, S. Graves, R. Heiberger, P. Krivitsky, R. Laboissiere, M. Maechler, G. Monette, D. Murdoch, H. Nilsson, and R-Core, *car: Companion to applied regression (Version 3.1-2)*, https://cran.r-project.org/web/packages/car/index.html, 2023.
- 99. R. W. Nahhas, An Introduction to R for Research. https://bookdown.org/rwnahhas/IntroToR/, 2025.
- 100. P. Allison, When can you safely ignore multicollinearity?, Statistical Horizons, 2012.
- 101. D. Darjana, S.K. Wiyono, and D.P. Koesrindartoto, Research on the impact of COVID-19 on the financial system: Evidence from Indonesia, PLOS ONE, vol. 20, no. 2, p. e0301123, 2025.
- 102. H. Guo, Y. Zhang, Y. Peng, T. Luo, and H. Wang, Does COVID-19 affect household financial behaviors? Fresh evidence from China, SAGE Open, vol. 12, no. 3, 2022.
- 103. J. Li, Q. Song, C. Peng, and Y. Wu, COVID-19 pandemic and household liquidity constraints: Evidence from micro data, Emerging Markets Finance and Trade, vol. 56, no. 15, pp. 3626–3634, 2020.

- 104. H. Ong, S. Wasiuzzaman, L. Chong, and S. Choon, *Digitalisation and financial inclusion of lower middle-income ASEAN*, Heliyon, vol. 9, no. 2, p. e13347, 2023.
- 105. F.H. Shihadeh, *How individual's characteristics influence financial inclusion: Evidence from MENAP*, International Journal of Islamic and Middle Eastern Finance and Management, vol. 11, no. 4, pp. 553–574, 2018.
- 106. R. Maulana and C. Nuryakin, The effect of saving account ownership and access to financial institutions on household loans in Indonesia, Bulletin of Monetary Economics and Banking, vol. 24, no. 3, pp. 465-486, 2021.
- 107. A. Suryani, Masyhuri, and L.R. Waluyati, Factors determining cassava farmers' accessibility to loan sources: Evidence from Lampung, Indonesia, Open Agriculture, vol. 8, no. 1, pp. 20220209, 2023.
- 108. S. Kumar and K. C. Pradhan, Socioeconomic and demographic determinants of financial inclusion in South Asia: Integrated policy for targeted groups of population, Journal of Policy Modeling, vol. 46, no. 3, pp. 655–682, 2024.
- 109. L. Klapper, D. Singer, and S. Ansar, *The Global Findex Database 2021 Women and financial inclusion*, The World Bank, Washington, D.C., 2022.
- 110. V. Botric and T. Broz, Gender differences in financial inclusion: Central and South Eastern Europe, South-Eastern Europe Journal of Economics, vol. 15, no. 2, pp. 209–227, 2017.
- 111. H. Morsy, Access to finance-Mind the gender gap, The Quarterly Review of Economics and Finance, vol. 78, pp. 12–21, 2020.
- 112. M. Johar and A. Rammohan, *The role of family networks and gender on borrowing behavior in Indonesia*, The Journal of Developing Areas, vol. 45, no. 1, pp. 111–134, 2011.
- 113. C. Okten and U. O. Osili, Social networks and credit access in Indonesia, World Development, vol. 32, no. 7, pp. 1225–1246, 2004.
- 114. K. Tsukada, T. Higashikata, and K. Takahashi, *Microfinance penetration and its influence on credit choice in Indonesia: Evidence from a household panel survey*, The Developing Economies, vol. 48, no. 1, pp. 102–127, 2010.
- 115. J. Vong, I. Song, R. D. Salian, R. Kariath, and K. Bunyong, *Improving the process of financial inclusion for women entrepreneurs in Indonesia*, International Journal of Process Management and Benchmarking, vol. 4, no. 2, pp. 167–185, 2014.
- 116. L. Cameron, *Gender equality and development: Indonesia in a global context*, Bulletin of Indonesian Economic Studies, vol. 59, no. 2, pp. 179–207, 2023.
- 117. T.W. Reynolds, P.E. Biscaye, C. Leigh Anderson, C. O'Brien-Carelli, and J. Keel, *Exploring the gender gap in mobile money awareness and use: Evidence from eight low and middle income countries*, Information Technology for Development, vol. 29, no. 2-3, pp. 228–255, 2023.
- 118. P.S. Puji and L. Hakim, Peran gender sebagai variabel moderating pembelajaran perbankan syariah, literasi keuangan syariah, religiusitas, inklusi keuangan syariah terhadap minat menabung bank syariah, Jurnal Pendidikan Akuntansi (JPAK), vol. 9, no. 1, pp. 1–12, 2021.
- 119. A. Carpio, Indonesian women as 'hidden financial managers.' Devpolicy Blog from the Development Policy Centre. https://devpolicy.org/indonesian-women-hidden-financial-managers-20171003/, October 2, 2017.
- 120. E. Frankenberg, J. P. Smith, and D. Thomas, *Economic shocks, wealth, and welfare*, The Journal of Human Resources, vol. 38, no. 2, pp. 280–321, 2003.
- 121. D. Rahardiani, P. Ward, S. Arif, and A. Carpio, *Understanding people's use of financial services in Indonesia: Headline Results Report*, Oxford Policy Management Ltd., Oxford, 2017.
- 122. Antara News, More women open bank accounts to access social aid: Ministry. Antara News. https://en.antaranews.com/news/196601/more-women-open-bank-accounts-to-access-social-aid-ministry, October 28, 2021.
- 123. S. E. O'Farrell and T. Warokka, *Indonesia's non-cash social assistance reform: An Analysis of TNP2K's Contribution*, MAHKOTA, Jakarta, 2018.
- 124. World Bank, Early experiences of beneficiary choice in government-to-person payment architecture in Indonesia, The World Bank, Washington, D.C., 2023.
- 125. L. Abdillah. An overview of Indonesian fintech application. In Proceedings of the First International Conference on Communication, Information Technology and Youth Study (I-CITYS2019), Melaka, Malaysia, 2019.
- 126. K.B. Maharani, H. Hudrasyah, and P.F. Belgiawan, Marketing strategy to increase brand awareness: A Study case on digital loan application, International Journal of Current Science Research and Review, vol. 6, no. 7, pp. 4579–4587, 2023.
- 127. B. Setiawan, D.P. Nugraha, A. Irawan, R.J. Nathan, and Z. Zoltan, *User innovativeness and fintech adoption in Indonesia*, Journal of Open Innovation: Technology, Market, and Complexity, vol. 7, no. 3, p. 188, 2021.
- 128. R. Sahay, U.E. von Allmen, A. Lahreche, P. Khera, S. Ogawa, M. Bazarbash, and K. Beaton, *The promise of fintech: Financial inclusion in the Post COVID-19 Era*, IMF Departmental Paper No. 2020/009, 2020.
- A. Awanis, C. Lowe, S.K. Andersson-Manjang, and D. Lindsey, State of the Industry Report on Mobile Money 2022. GSM Association, London, 2022.
- 130. K. Davis, R. Maddock, and M. Foo, *Catching up with Indonesia's fintech industry*, Law and Financial Markets Review, vol. 11, no. 1, pp. 33–40, 2017.
- 131. A. Mouna and A. Jarboui, Understanding the link between government cashless policy, digital financial services and sociodemographic characteristics in the MENA countries, International Journal of Sociology and Social Policy, vol. 42, no. 5-6, pp.
- 132. L. Judijanto, R. Ariyanti, and S. Suryani. Analysis of the impact of mobile banking technology, fintech, and digital transaction security on customer loyalty at BUMN Banks in Indonesia, West Science Social and Humanities Studies, vol. 2, no. 08, pp. 1299–1309, 2024.
- 133. J.T. Purba, S. Samuel, and S. Budiono, Collaboration of digital payment usage decision in COVID-19 pandemic situation: Evidence from Indonesia, International Journal of Data and Network Science, vol. 5, pp. 557–568, 2021.
- 134. R. Damayanti, D. Pramesti, L. Ayuninggar, E. Martini, and M. Rosdaliva, *Readiness for digital financial transformation: The case of micro, small and medium enterprises in Indonesia*, International Journal of Economics and Management, vol. 19, no. 1, pp. 57–66, 2025
- 135. D.P. Nugraha, B. Setiawan, R.J. Nathan, and M. Fekete-Farkas, *Fintech adoption drivers for innovation for SMEs in Indonesia*, Journal of Open Innovation: Technology, Market, and Complexity, vol. 8, no. 4, p. 208, 2022.

- S. Garz, X. Giné, D. Karlan, R. Mazer, C. Sanford, and J. Zinman, Consumer protection for financial inclusion in low- and middle-income countries: Bridging regulator and academic perspectives, Annual Review of Financial Economics, vol. 13, no. 1, pp. 219

  246, 2021.
- 137. E. Junarsin, R.Y. Pelawi, J. Kristanto, I. Marcelin, and J.B. Pelawi, *Does fintech lending expansion disturb financial system stability?* Evidence from Indonesia, Heliyon, vol. 9, no. 9, p. e18384, 2023.
- 138. R. Yudaruddin, W. Soedarmono, B.A. Nugroho, Z. Fitrian, P. Mardiany, A.H. Purnomo, and E.N. Santi, *Financial technology and bank stability in an emerging market economy*, Heliyon, vol. 9, no. 5, p. e16183, 2023.
- 139. I. E. Pratiwi, Financial inclusion in Indonesia: Does education matter? Economics and Sociology, vol. 16, no. 1, pp. 265–281, 2023.
- 140. A. N. Rini and L. Rahadiantino, *Financial inclusion of households in Indonesia*, International Journal of Business and Society, vol. 24, no. 2, pp. 832–845, 2023.
- 141. P. I. Eka, Financial inclusion in Indonesia: Does education matter?, Economics and Sociology, vol. 16, no. 1, pp. 265–281, 2023.
- 142. S. Ansar, L. Klapper, and D. Singer, *The importance of financial education for the effective use of formal financial services*, Journal of Financial Literacy and Wellbeing, vol. 1, no. 1, pp. 28–46, 2023.
- 143. R. Hidayat and R. L. Sari, *Linkage between financial inclusion and Indonesian welfare: A recent evidence*, Cogent Business & Management, vol. 9, no. 1, pp. 2108299, 2021.
- 144. A. Suleiman, T. Dewaranu, and N. H. Anjani, *Creating informed consumers: Tracking financial literacy programs in Indonesia. Policy Paper No.* 49, Center for Indonesian Policy Studies (CIPS), Jakarta, 2022.
- 145. U. Widyastuti, D. K. Respati, V. I. Dewi, and A. M. Soma, *The nexus of digital financial inclusion, digital financial literacy and demographic factors: Lesson from Indonesia*, Cogent Business & Management, vol. 11, no. 1, pp. 2322778, 2024.
- 146. A. Wardhono, M. A. Nasir, C. G. Qori'ah, and K. I. Sari, *Financial literacy and inclusion on consumption in Indonesian rural communities*, Economics Development Analysis Journal, vol. 11, no. 3, pp. 370–380, 2022.
- 147. J. S. Lopus, D. S. Amidjono, and P. W. Grimes, *Improving financial literacy of the poor and vulnerable in Indonesia: An empirical analysis*, International Review of Economics Education, vol. 32, pp. 100168, 2019.
- 148. M. M. Amalia, *Determining factors for the success of digital financial inclusion in industrial estates in Indonesia*, West Science Journal Economic and Entrepreneurship, vol. 3, no. 1, pp. 62–69, 2025.
- 149. A. Lusardi and O. S. Mitchell, *The economic importance of financial literacy: Theory and evidence*, Journal of Economic Literature, vol. 52, no. 1, pp. 5–44, 2014.
- 150. P. J. Morgan and L. Q. Trinh, *Determinants and impacts of financial literacy in Cambodia and Viet Nam*, Journal of Risk and Financial Management, vol. 12, no. 1, pp. 19, 2019.
- 151. U. Inyang, Risks to credit access in a developing economy: Focus on household characteristics and the choice of credit in the Niger Delta Region of Nigeria, International Journal of Research in Business and Social Science (2147-4478), vol. 11, no. 2, pp. 228–240, 2022
- 152. T.N. Linh, H.T. Long, L.V. Chi, L.T. Tam, and P. Lebailly, Access to rural credit markets in developing countries, the case of Vietnam: A literature review, Sustainability, vol. 11, no. 5, p. 1468, 2019.
- 153. M.T. Bui and T.N.O. Luong, Financial inclusion for the elderly in Thailand and the role of information communication technology, Borsa Istanbul Review, vol. 23, no. 4, pp. 818–833, 2023.
- 154. B.B. Balana and M.A. Oyeyemi, Agricultural credit constraints in a smallholder farming in developing countries: Evidence from Nigeria, World Development Sustainability, vol. 1, p. 100012, 2022.
- 155. A. De Brauw, S. Herskowitz, K. Ambler, B. Sayaka, S. Pasaribu, F. Dabukke, Suhartini, E. Suryani, A. Suwarno, and T. Moyes, *Agricultural value chain finance in Indonesia*. International Food Policy Research Institute (IFPRI), Washington, DC, 2021.
- 156. T. L. H. Putri, Analysis of credit risk differences based on risk management and related banking regulation: Case study of banks in Indonesia and Malaysia, Owner: Riset dan Jurnal Akuntansi, vol. 9, no. 1, pp. 162–178, 2025.
- 157. R. Hidayati and N. M. Rachman, *Indonesian government policy and SME's business strategy during the Covid-19 pandemic*, Niagawan, vol. 10, no. 1, pp. 1–9, 2021.
- 158. D. Darjana, S. K. Wiryono, and D. P. Koesrindartoto, *The COVID-19 pandemic impact on banking sector*, Asian Economics Letters, vol. 3, no. 3, pp. 1–6, 2022.
- 159. S. Safuan, E. A. Sugandi, M. S. Habibullah, and G. A. James, *Analyzing monetary policies and bank credit in Indonesia's provincial clusters amidst COVID-19 pandemic*, Journal of the Asia Pacific Economy, vol. 29, no. 4, pp. 1785–1833, 2024.
- 160. A. Aziz and S. Maulida, *Bank credit growth in Indonesia during the Covid-19 pandemic and its regulations*, Journal of Central Banking Law and Institutions, vol. 3, no. 1, pp. 177–202, 2024.
- 161. R. Nanang, W. Dyah, S. Sri, and S. N. Yesi, *The impact of Covid-19 pandemic on banks in Indonesia: Comparative analysis*, Eksis: Jurnal Riset Ekonomi dan Bisnis, vol. 17, no. 2, pp. 211–224, 2023.
- 162. D. Silaswara, I. Gunawan, and T. S. Fung, Analysis of money circulating in Indonesia during Covid-19 pandemic, Primanomics: Jurnal Ekonomi & Bisnis, vol. 18, no. 3, pp. 36–46, 2020.
- 163. H. S. Disemadi and A. I. Shaleh, *Banking credit restructuring policy amid COVID-19 pandemic in Indonesia*, Jurnal Inovasi Ekonomi, vol. 5, no. 2, pp. 63–70, 2020.
- 164. D. Pangaribowo, F. Rosalia, M. Mukhlis, F. Novriansyah, and N. Poniasih, *The effectiveness of the Indonesian government's economic stimulus policy during the Covid-19 pandemic*, Jurnal Public Policy, vol. 8, no. 1, pp. 36–40, 2022.
- 165. A. Alfonso, Pengaruh penyaluran kredit dan restrukturisasi kredit terhadap kinerja non-performing loan pada Himbara selama pandemi Covid-19 (Periode 2020-2022), JPEKA: Jurnal Pendidikan Ekonomi, Manajemen dan Keuangan, vol. 7, no. 1, pp. 79–93, 2023
- 166. R. I. Lestari, D. Santoso, and I. Indarto, *Meningkatkan literasi keuangan digital pada pelaku UMKM melalui sosialisasi gerakan nasional non-tunai*, Jurnal Inovasi Hasil Pengabdian Masyarakat (JIPEMAS), vol. 4, no. 3, pp. 378–390, 2021.
- 167. A. Agusti, D. Edriani, and A. Ilyas, *Financial empowerment for women: Closing the gender wealth gap*, Equator Journal of Management and Entrepreneurship, vol. 12, no. 3, pp. 251–259, 2023.

- 168. A. D. Angreyani, A. Akbar, M. I. M. Haeruddin, M. Y. Mustafa, and F. Mustafa, *The phantom menace: A moderation analysis of gender on MSMEs' financial literacy and financial performance*, Asian Research Journal of Arts & Social Sciences, vol. 21, no. 2, pp. 48–55, 2023.
- 169. Y. Afrida, I. Abdullah, Z. H. Prasojo, M. Ulfah, P. A. Saka, and J. Nelli, *Economic empowerment of unbanked women through financial inclusion in Indonesia*, Cogent Business & Management, vol. 11, no. 1, pp. 2407921, 2024.
- 170. B. Setiawan, T. D. Phan, J. Medina, M. Wieriks, R. J. Nathan, and M. Fekete-Farkas, *Quest for financial inclusion via digital financial services (Fintech) during COVID-19 pandemic: Case study of women in Indonesia*, Journal of Financial Services Marketing, vol. 29, pp. 459–473, 2023.
- 171. S. Soekarno, I. Y. Mambea, and M. Setiawati, Women and digital financial inclusion in Indonesia as emerging market, International Review of Management and Marketing, vol. 10, no. 5, pp. 46–49, 2020.
- 172. J. Vong and I. Song, Emerging Technologies for Emerging Markets, Springer, Singapore, 2015.
- 173. A. Arwani, S. D. Rismawati, H. Ma'shum, Z. Mustakim, K. Ismanto, H. R. Devy, M. Rosyada, and F. Rohmah, *Women's economic transformation: A literature review on empowerment through entrepreneurship and financial inclusion in Pekalongan, Indonesia*, International Journal of Religion, vol. 5, no. 10, pp. 4056–4069, 2024.
- 174. A. M. Igamo, R. A. Rachmat, M. I. Siregar, M. I. Gariba, V. Cherono, A. S. Wahyuni, and B. Setiawan, *Factors influencing Fintech adoption for women in the post-Covid-19 pandemic*, Open Innovation: Technology, Market, and Complexity, vol. 10, no. 1, pp. 100236, 2024.
- 175. Farida, S. Binastuti, W. Silfianti, and B. Hermana, *The impact of Covid-19 on electronic payment system: Lesson learned from Indonesian banking*, Technium Social Sciences Journal, vol. 40, no. 1, pp. 200–212, 2023.
- 176. T. Dahlhaus, and A. Welte, *Payment habits during Covid-19: Evidence from high-frequency transaction data*, Jahrbücher Für Nationalökonomie Und Statistik, vol. 245, no. 6, pp. 599–621, 2025.
- 177. H. M. Aji, I. Berakon, M. Md Husin, and A. W. K. Tan, *COVID-19 and e-wallet usage intention: A multigroup analysis between Indonesia and Malaysia*, Cogent Business & Management, vol. 7, no. 1, p. 1804181, 2020.
- 178. D. M. Immanuel and Y. K. Dewi, *Mobile money adoption intention during pandemic COVID-19 in Indonesia*, Journal of Information System and Technology Management (JISTM), vol. 5, no. 19, pp. 60–76, 2020.
- 179. W. Rafdinal and W. Selasari, *Predicting the adoption of mobile payment applications during the COVID-19 pandemic*, International Journal of Bank Marketing, vol. 39, no. 6, pp. 984–1002, 2021.
- 180. T. Sendjaja, D. J. Rachbini, R. Astini, and D. Asih, *The Effectiveness of QRIS Transaction Implementation During the COVID-19 Pandemic*, International Journal of Science and Society (IJSOC), vol. 5, no. 5, 2023.
- 181. B. E. Akinyemi and A. Mushunje, *Determinants of mobile money technology adoption in rural areas of Africa*, Cogent Social Sciences, vol. 6, no. 1, pp. 1815963, 2020.
- 182. D. Krupa and M. Buszko, Age-dependent differences in using FinTech products and services—Young customers versus other adults, PLOS ONE, vol. 18, no. 10, pp. e0293470, 2023.
- 183. H. Cahyadi, R. P. Tarigan, R. R. Masman, E. Trisnawati, and H. Wijaya, Exploring the dynamics of fintech usage behavior moderated by customer characteristics in Indonesia, International Journal of Innovative Research and Scientific Studies, vol. 7, no. 3, pp. 997– 1008, 2024.
- 184. P. Christiaan, O. Rosalia, F. Firayani, and A. Noviya, *The role of Financial Technology (Fintech) in Improving Financial Literacy and Inclusion in Indonesia*, Maneggio, vol. 2, no. 1, pp. 258–267, 2025.
- 185. F. Marisya, M. Marsinah, and R. Wahasusmiah, Fintech Developments in Indonesia: A Critical Multiperspective Analysis Review, Journal of Management and Creative Business, vol. 3, no. 1, pp. 465–486, 2021.
- 186. A. Meilasari-Sugiana, S. D. Negara, and H. Yew-Foong, Financial technology adoption in Greater Jakarta: patterns, constraints and enablers. ISEAS Publishing, Singapore, 2022.
- 187. S. Chen, S. Doerr, J. Frost, L. Gambacorta, and H. S. Shin, *The fintech gender gap*, Journal of Financial Intermediation, vol. 54, p. 101026, 2023.
- 188. A. Ram, *Understanding FinTech Gender Gap: A Survey on Financial Literacy, Inclusion and FinTech Use*, Open Journal of Business and Management, vol. 11, no. 6, pp. 3518–3538, 2023.
- 189. H. E. Moghadam and A. Karami, Financial inclusion through FinTech and women's financial empowerment, International Journal of Social Economics, vol. 50, no. 8, pp. 1038–1059, 2023.
- 190. A. K. Yeyouomo, S. A. Asongu, P. Agyemang-Mintah, Fintechs and the financial inclusion gender gap in Sub-Saharan African countries, Women's Studies International Forum, vol. 97, p. 102695, 2023.
- 191. D. Akata, *The Effect of COVID-19 on Electronic Currencies as They Become Common Payment Methods*, In Pandemnomics: The Pandemic's Lasting Economic Effects, edited by B. Açikgöz and I. A. Acar, Springer Nature, Cham, Switzerland, pp. 221–237, 2022.
- 192. J. Hellemans, K. Willems, and M. Brengman, Covid-19 and mobile payment in Belgium: Closing the digital divide or just for the young, social, and impulsive?, Electronic Commerce Research, vol. 23, no. 3, pp. 1539–1564, 2023.
- 193. N. Upadhyay, S. Upadhyay, S. S. Abed, and Y. K. Dwivedi, Consumer adoption of mobile payment services during COVID-19: extending meta-UTAUT with perceived severity and self-efficacy, International Journal of Bank Marketing, vol. 40, no. 5, pp. 960–991, 2022.
- 194. Yu and Chen, Consumers' Switching from Cash to Mobile Payment under the Fear of COVID-19 in Taiwan, Sustainability, vol. 14, no. 14, p. 8489, 2022.
- 195. Y. Zhao and F. Bacao, *How Does the Pandemic Facilitate Mobile Payment? An Investigation on Users' Perspective under the COVID-19 Pandemic*, International Journal of Environmental Research and Public Health, vol. 18, no. 3, p. 1016, 2021.
- 196. H. Mansour, How successful countries are in promoting digital transactions during COVID-19, Journal of Economic Studies, vol. 49, no. 3, pp. 435–452, 2022.
- 197. W. D. Bekele, Contactless digital financial innovation and global contagious COVID-19 pandemic in low income countries: Evidence from Uganda, Cogent Economics & Finance, vol. 11, no. 1, p. 2175467, 2023.
- 198. D. D. Sjoberg, K. Whiting, M. Curry, J. A. Lavery, and J. Larmarange, *Reproducible summary tables with the gtsummary package*, The R Journal, vol. 13, no. 1, pp. 570–580, 2021.

- 199. X. Robin, N. Turck, A. Hainard, N. Tiberti, F. Lisacek, J.-C. Sanchez, and M. Müller, pROC: An open-source package for R and S+ to analyze and compare ROC curves, BMC Bioinformatics, vol. 12, no. 1, p. 77, 2011.
- 200. I.U. Wani, M. Alharthi, I.N. Khanday, M. Subhan, and M.A.S. Al-Faryan, Exploring the complementary interaction between financial inclusion and gender equality on economic growth: Fresh evidence from developing countries, Cogent Economics & Finance, vol. 12, no. 1, p. 2365585, 2024.
- 201. W. H. Greene, *Econometric Analysis (7th ed.)*, Pearson Education, Inc., Hoboken, New Jersey, 2012. 202. D. A. Newman, *Missing data: Five practical guidelines*, Organizational Research Methods, vol. 17, no. 4, pp. 372–411, 2014.
- 203. K. Song, P. Wu, and S. Zou, The adoption and use of mobile payment: Determinants and relationship with bank access, China Economic Review, vol. 77, pp. 101907, 2023.