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

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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, formal saving, formal 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

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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)

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[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 March 2, 2020 [42]. Then on March 31 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][1]. 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,

[1] 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]:[2] (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 `https://doi.org/10.48529/fkzs-at21` and `https://doi.org/10.48529/jq97-aj70`. 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, and the interviews for the 2021 round were conducted from July 7 to October 15, 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 `http://microdata.worldbank.org`. The World Bank has removed any information that could be used to identify the respondents. Therefore, no additional ethical clearance was required.

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[2] On page 15 of Rogers [58].

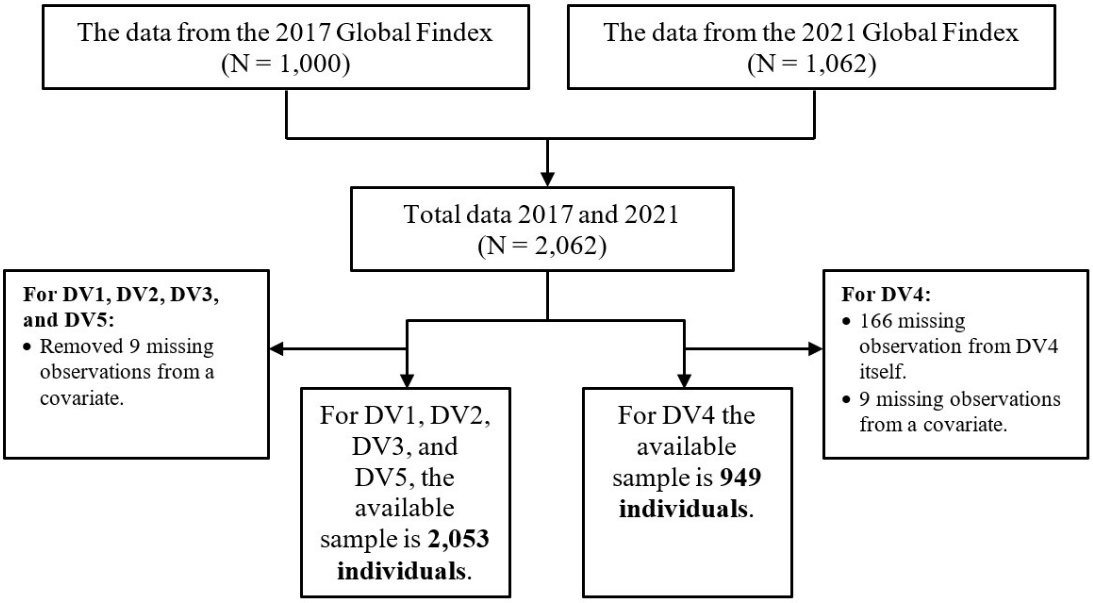

Figure 1. Flow diagram of the sample selection (unweighted sample).
Notes: DV = Dependent variable; DV1 = *account*; DV2 = *saving*; DV3 = *credit*; DV4 = *mobintpay*; DV5 = *mmoney*; See Table 1 for more details.

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.[3] 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].[4] 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].[5] 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].[6]

[3]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].
[4]on page 2 of [67].
[5]on page 2 of [67].
[6]on page 2 of [67].

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 indicators 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`
Dependent variables – use of financial technologies		
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:		

Continued on next page

Table 1 – continued from previous page

Variables	Description	Code
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`
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).	`year2c`

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]:

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

where b_0 is the intercept, b_1 to b_{10} are the estimated coefficients, and ε_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:

$$\begin{aligned}\frac{P_i}{1-P_i} = {} & \exp(b_0) \times \exp(b_1)\textit{female}_i \times \exp(b_1)\textit{age}_i \times \exp(b_2)\textit{age}_i^2 \times \exp(b_3)\textit{educ\_secondary}_i \times \\ & \exp(b_4)\textit{educ\_tertiary}_i \times \exp(b_5)\textit{income\_q2}_i \times \exp(b_6)\textit{income\_q3}_i \times \\ & \exp(b_7)\textit{income\_q4}_i \times \exp(b_8)\textit{income\_q5}_i \times \exp(b_9)\textit{mphone}_i \times \exp(b_{10})\textit{year}_i \end{aligned} \tag{2}$$

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:

1. AMEs address the misinterpretation of ORs as RRs.
2. 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.
3. 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:

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

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:

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

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) [88]. 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 [89][7] argues that the number of repetitions for multiple imputation can be set to the average 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 [90, 91]. These were done using "mice" [92] and "mitools" package [93].

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 [94]. 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 [95, 96]. The Tjur R^2 is formulated as follows:

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

where $\bar{\hat{p}}_1$ and $\bar{\hat{p}}_0$ 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 [96] 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 [97]. 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]:

[7] page 61 of Van Buuren [89].

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

To address possible collinearity issues, we assessed the generalized variance inflation factor (GVIF) using the "car" package [74, 98, 99]. Although no clear-cut answers exist to how large a GVIF value we need to worry about, there are some expert guidelines [100]. Allison [101] 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) [100]. 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 [100]. 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 [100, 101].

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 [101].

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.

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

Variables	Financial account	Borrowed in the past year	Saved in the past year	Paid using mobile phone or Internet[1]	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

[1]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.
Abbreviation: GVIF = generalized variance inflation factor.
Note: the GVIFs above are adjusted for degrees of freedom.
Source: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

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 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, 102]. Such contractions are consistent with the finding that households faced income shocks and reduced borrowing due to tighter credit conditions during the pandemic [103, 104].

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 [105], 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 saving 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 [106].

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 [103, 104]. Despite stable account ownership, this decline suggests a shift towards short-term liquidity over long-term savings.

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 [107, 108]. Borrowing declined during the pandemic compared to before the pandemic by 12.5 percentage points, indicating cautious financial behavior and stricter lending standards [104].

Studies related to financial inclusion have shown nonlinear relationships between age and financial inclusion indicators [10, 24, 109]. 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.[8] 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 the formal credit, a more marked U-shaped relationship between age and the probability of borrowing is evident, peaking at the age of 39 years.[9] 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 saving, there is no statistically significant evidence of a nonlinear relationship with respect to age.

[8] The estimated coefficients of logit regression models pertaining to main financial indicators can be found in Table A3 in the Appendix.
[9] 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).

Table 3. Unweighted and weighted summary statistics for study variables.

Variables	**Unweighted**			**Weighted**		
	Total (N = 2,062)	**2017** (N = 1,000)	**2021** (N = 1,062)	**Total**	**2017**	**2021**
Dependent variables – 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%)
Dependent variables – use of financial technologies						
Used mobile phone or the 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%)

Continued on next page

Table 3 – continued from previous page

Variables	Unweighted			Weighted		
	Total (N = 2,062)	**2017** (N = 1,000)	**2021** (N = 1,062)	**Total**	**2017**	**2021**
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%)
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].

Table 4. Factors associated with main financial inclusion indicators in Indonesia.

Variables	**Formal account**		**Formal saving**		**Formal credit**	
	AME[1]	**SE**	**AME**[1]	**SE**	**AME**[1]	**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
Highest education (ref: Primary or less)						
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	2,053		2,053		2,053	
Tjur's R^2	0.156		0.170		0.069	
AUC	0.731		0.738		0.652	

[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].

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, 110]. However, there are no significant gender-based differences in formal saving behavior [110]. Global and regional evidence suggests that women continue to face structural barriers in accessing formal financial services [111, 112]. The analysis in this study observed that women are more likely to have formal accounts (AME $= 0.076$) and to make 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 [113, 114, 115, 116]. However, sociocultural norms, limited income opportunities, informal employment, and gaps in financial literacy hinder broader access to formal services [117, 118, 119]. 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 [120, 121, 122]. 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

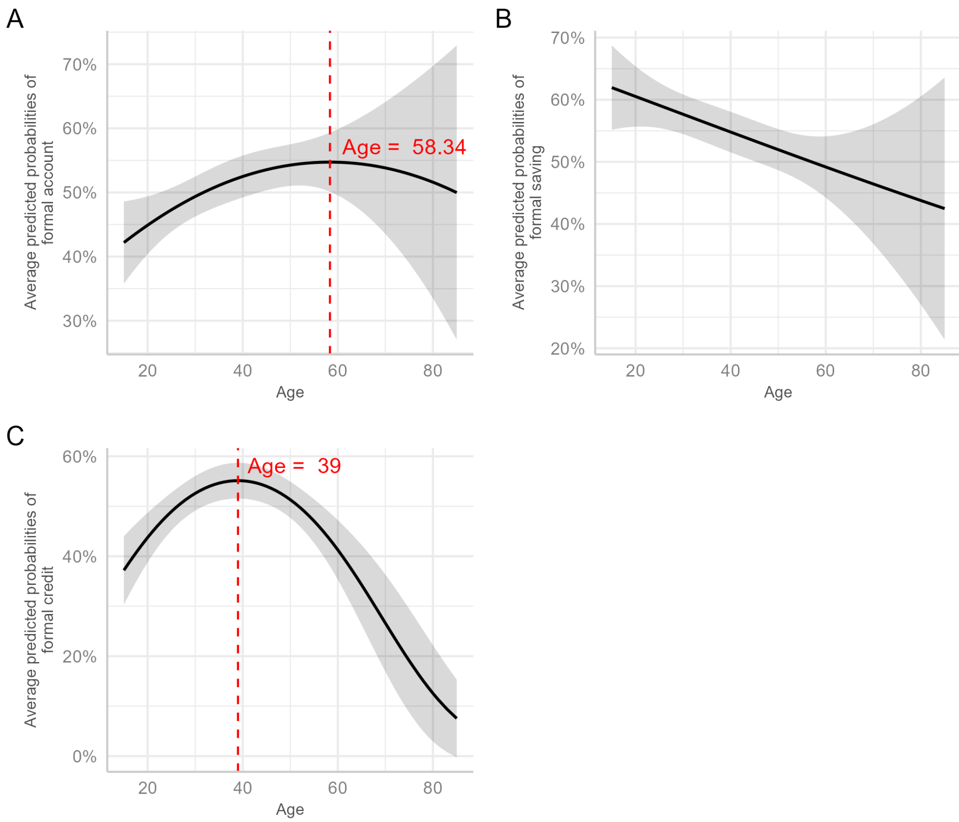

Figure 2. Average predicted probabilities of formal account (A), formal saving (B), and formal credit (C).
Source: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

designed to be directly transferred to the female household member. These women must have a formal bank account to receive assistance [123, 124, 125].

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 [126, 127, 128]. This finding aligns with global evidence from the Global Findex 2021 and IMF studies [3, 129, 130] and recent findings that show that FinTech adoption contributes to narrowing income-related inequalities in financial services [20].

In Indonesia, high mobile penetration (85%) compared to lower active internet use (64.8%) [131] 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 [132], initiatives such as the Quick Response Code Indonesian Standard (QRIS)[10] and peer-to-peer (P2P) lending regulation[11] accelerated the shift toward digital financial platforms. The pandemic further fueled mobile-based transactions, as consumers prioritized speed, convenience, and safety [133, 134]. Fintech innovations and digital banking have leveraged this trend to serve micro, small, and medium enterprises (MSMEs) and the unbanked more effectively [135, 136]. However, the rapid expansion of FinTech lending also

[10] Bank Indonesia Circular Letter No.21/25/DKSP of 2020 concerning implementation of QRIS.
[11] Regulation of the Financial Services Authority No. 77/POJK.01 of 2016 concerning Information Technology-Based Money Lending Services.

raises systemic risks and challenges for conventional risk management, highlighting the need for stronger consumer protection frameworks and prudential oversight [137, 138, 139].

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 making formal 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, 140, 141]. These findings align with those of Eka [142], who highlighted that education significantly improves financial literacy and the ability to utilize formal financial services effectively. Similarly, Ansar et al. [143] 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 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 [144, 145, 146]. Improving financial literacy has been shown to enhance saving behavior, digital financial usage, and prudent financial decision-making, even among rural and vulnerable populations [147, 148]. 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 [146, 149]. 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 [150, 151].

Age dynamics add another dimension to this issue. While age has no significant effect on formal account ownership or formal saving behavior, supporting the saturation hypothesis, its influence on credit is nonlinear, with borrowing peaking in productive ages and declining at older ages [152, 153]. 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 information, communication, and technology-based financial services, a challenge also relevant to Indonesia's shift to digital financial ecosystems [154]. For vulnerable groups, such as smallholder farmers or low-income households, income volatility and risks, such as climate shocks, further restrict access [155, 156]. Banks adopt conservative lending strategies and prioritize lower-risk segments to balance profitability and risk [157].

The COVID-19 pandemic exerted mixed effects; account ownership remained stable, but formal saving and credit contracts as households prioritized liquidity and reduced borrowing [103, 104]. 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 [158, 159, 160]. 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 [159, 160, 161, 162]. Although some households increased their precautionary savings in response to uncertainty, aggregate savings growth slowed due to widespread income reduction [162, 163].

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*).[12] In response to the pandemic, the government implemented several measures to stabilize the

[12]Regulation of the Financial Services Authority No. 19/POJK.03 of 2014 and No. 1/POJK.03 of 2022 concerning *Laku Pandai*.

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 [162, 164, 165], 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 [158, 165]. 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 [165, 166].

Meanwhile, the GNNT accelerated the adoption of non-cash transactions and digital financial services across sectors, including MSMEs, enhancing transaction efficiency and financial access [167]. 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 to utilizing these services effectively, underscoring the critical role of financial education in strengthening inclusive financial resilience [150, 151].

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 [168, 169]. Integrated training and mentoring programs linked to access to financial products can further strengthen women's confidence and financial decision-making [170]. 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 [171, 172, 173]. 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 [174, 175].

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.[13] 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.

[13] See Table A4 in the Appendix for the coefficients of the logit regression.

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 [176, 177]. Studies have cited health concerns as one of the drivers of digital payment use [178, 179, 180]. 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 [176]. 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 [181]. Nonetheless, the results show significantly higher probabilities of using mobile money services during the pandemic than before.

Table 5. Factors associated with use of financial technologies in Indonesia.

Variables	**Payment using mobile**[1]		**Mobile money services**	
	AME[2]	**SE**	**AME**[2]	**SE**
Female (ref: No)				
Yes	0.013	0.028	0.011	0.012
Age	-0.007***	0.002	-0.003**	0.001
Highest education (ref: Primary or less)				
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	

[1] Results from a pooled set of 30 times imputation using Rubin's rule, using the mean for Tjur's R^2 and AUC.
[2] $^+p < .1$; $^*p < .05$; $^{**}p < 0.01$; $^{***}p < .001$.
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].

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 [182, 183]. 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 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%.

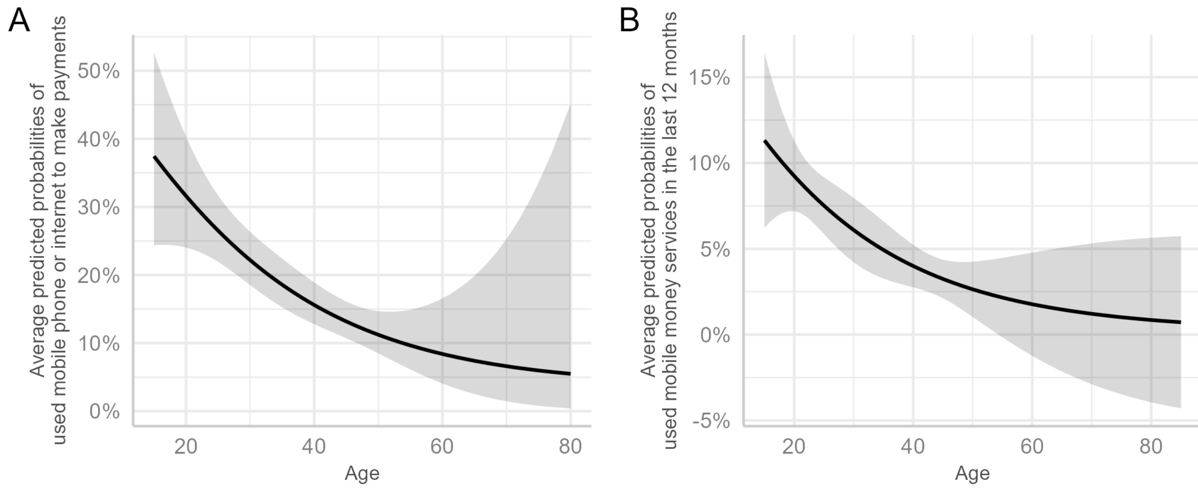

Figure 3. Average predicted probabilities of *mobintpay* (A) and *mmoney* (B).
Source: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

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 [184, 185]. This finding aligns with those of Eka [142] and Ansar et al. [143], 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 [185, 186]. 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 [187].

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 [188, 189]. Fintech alone cannot eliminate these disparities without targeted interventions, such as digital literacy programs tailored to women and inclusive platform design [190, 191].

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, 178, 192, 193, 194, 195, 196]. 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 [181], 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 [197, 198].

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 Figure A1 and Figure 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 saving 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 saving behavior, 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.

The results of this study 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 utilize micro-level panel data to investigate the long-term effects of financial inclusion on household resilience, poverty reduction, and entrepreneurship, particularly in the 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.

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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://github.com/aripurwantosp/covid19_financial_inclusion_findex_indonesia_data_analysis.

A. Appendix: Data Analysis

A.1. Percentages of missing values in the fourth dependent variable ("mobintpay")

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

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

A.2. 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		2021	
	Coef[1]	SE	Coef[1]	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
Observations	535		579	

[1] $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Abbreviations: Coef = Logistic regression coefficient (log-odds); SE = Standard Error.

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

A.3. Coefficients of logit regression model of main financial inclusion indicators

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

Variables	Formal account			Formal saving			Formal credit		
	Coef[1]		SE	Coef[1]		SE	Coef[1]		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
Highest education (ref: Primary or less)									
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 R^2	0.156			0.170			0.069		
AUC	0.731			0.738			0.652		

[1] $^{+}p < .1$; $^{*}p < .05$ $^{**}p < .01$; $^{***}p < .001$.

Abbreviations: Coef = Logistic regression coefficients; SE = Standard Error; AUC = Area Under the ROC Curve.

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

A.4. 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[1]	SE	Coef[1]	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
Highest education (ref: Primary or less)				
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 +	0.415	0.558	0.391
Currently employed (ref: No)				
Yes	0.050	0.238	0.479 +	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	1114		2053	
Tjur's R^2	0.173		0.146	
AUC	0.779		0.866	

[1] $^{+}p < .1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$
Abbreviation: Coef = Logistic regression coefficient; SE = Standard Error; AUC = Area Under the ROC Curve.
Source: Authors' calculations of the 2017 and 2021 Global Findex data [48, 49].

A.5. Sensitivity analyses of main financial inclusion models

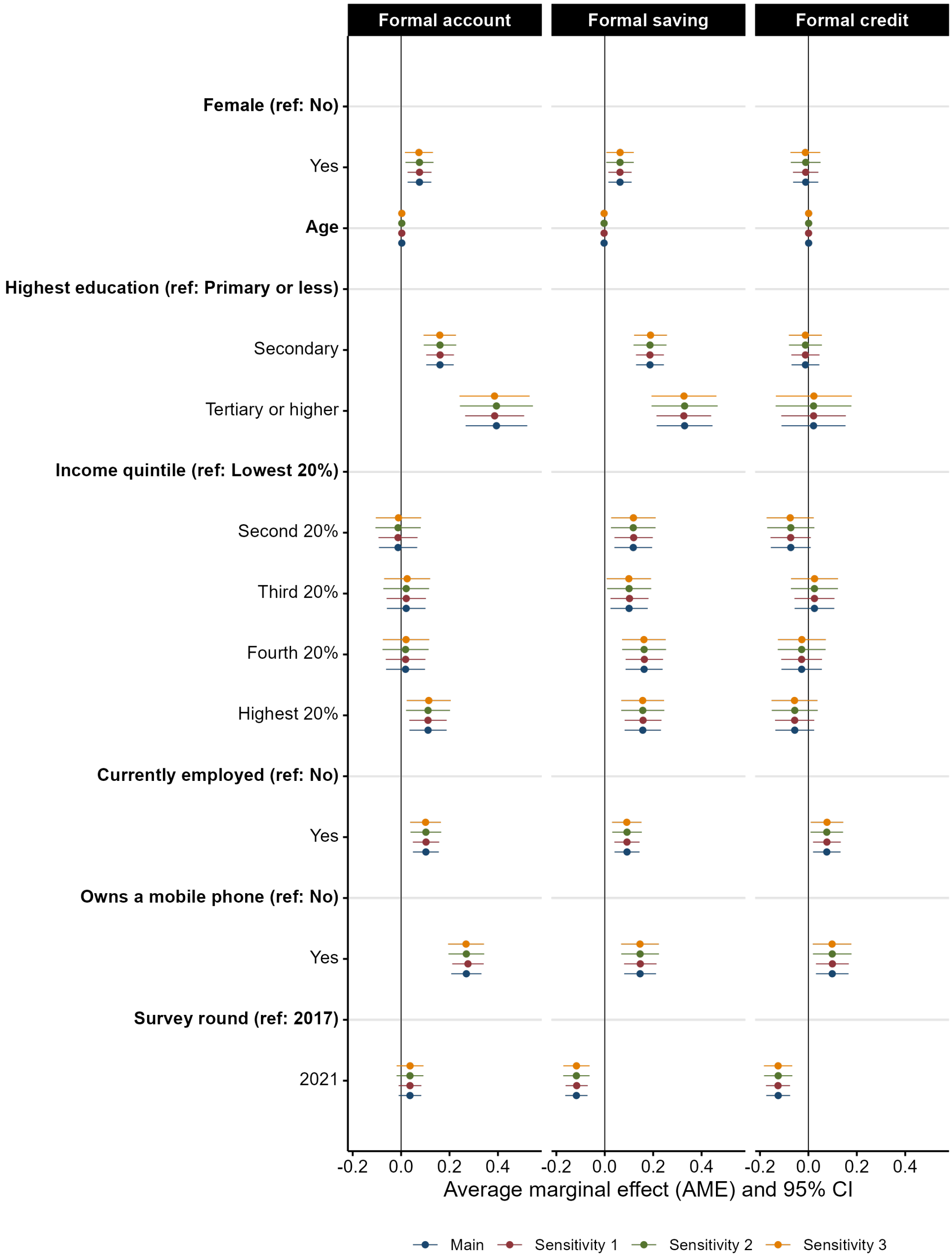

Figure A1. Results of sensitivity analyses of the main financial inclusion indicators.

A.6. Sensitivity analyses of the use of financial technology models

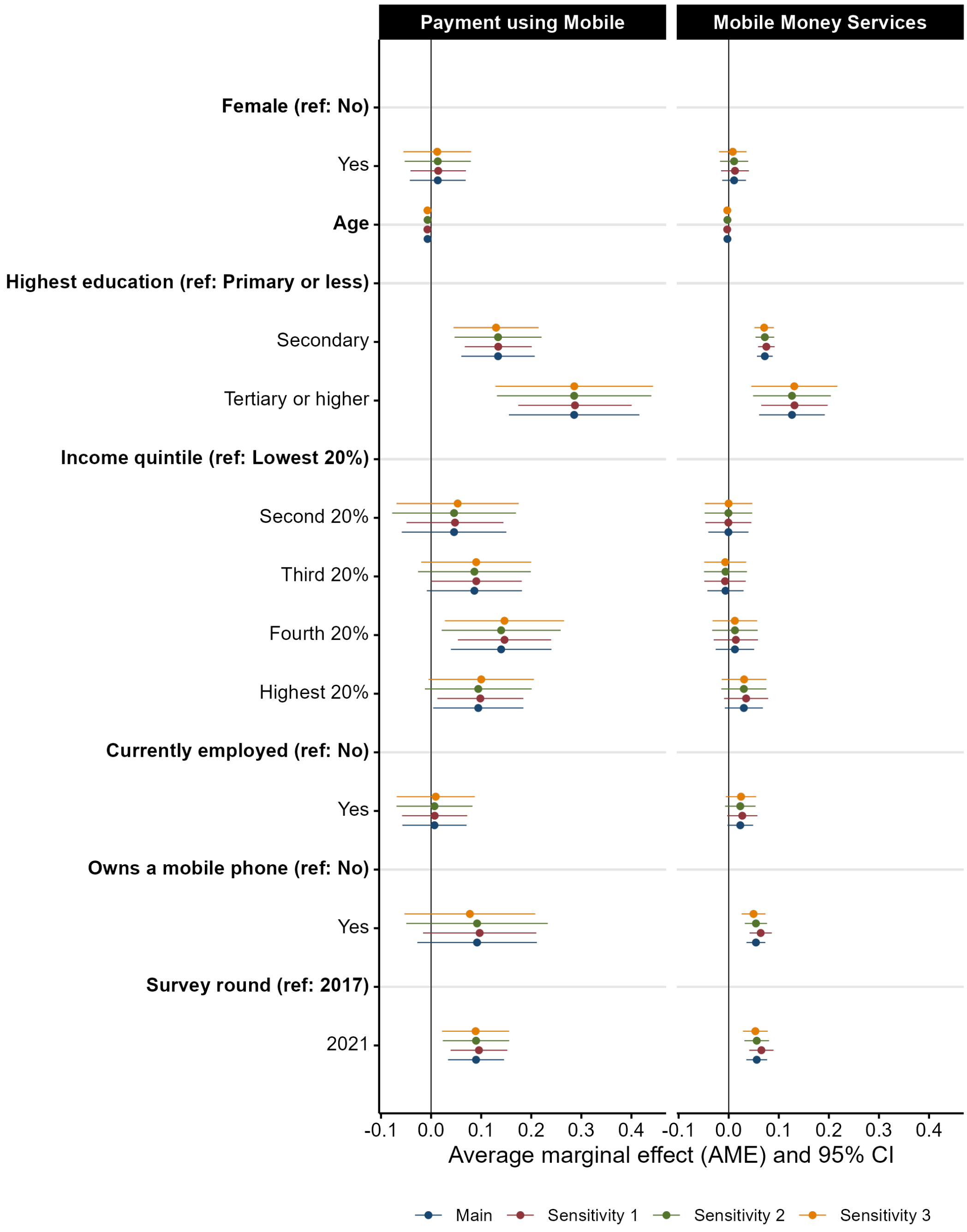

Figure A2. Results of sensitivity analyses of the use of financial technologies.

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