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Identifying the Barriers to Digital Financial Inclusion in The Most Financially Excluded Country Using Machine Learning Algorithm

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Abstract - Despite the call of digital financial services (DFS) to improve inclusive growth and reduce poverty, the adoption of DFS remains low in Nigeria. The objective of this study is to examine the barriers of ability, access and usage of DFS in Nigeria. This study uses secondary data Global Findex year 2017 and year 2021 to predict the socioeconomic factors on the target variables of DFS (ability, access and usage). Using a machine learning (ML) algorithm, namely the J48 decision tree in the Waikato Environment for Knowledge Analysis (WEKA) software, this study analyses the predictive strength of variables such as gender, education, income quintile, employment status, and urbanicity in determining ability, access to and usage of DFS. The main findings from the results show that the J48 decision tree demonstrates improvement in correctly classifying instances for year 2017 data to the year 2021 data. The root nodes for all sets of data show that education is the main predictor for DFS. The first-level split is gender for DFS when the target variables are ability and usage but is age when the target variable is access. Results show that education is the main barrier of DFS whereas gender and age are the secondary impediments to the adoption of DFS. Policymakers can benefit from the findings of this study to design targeted interventions—such as increasing their education level and organizing more digital financial literacy programs to accelerate DFS adoption among marginalized groups. The novelty of this study is to utilize a ML algorithm to identify the barriers of DFS and its accuracy rate has increased from the results of using the year 2017 data to the year 2021 data. By exploring key determinants through ML, this study contributes to the broader agenda of financial inclusion and promotes the accomplishment of sustainable development goals.

Keywords—J48 Decision Tree, Ability, Access, Usage, Digital Financial Service, Machine Learning

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1. INTRODUCTION

Financial inclusion is defined as the access to and use of formal financial services [1]. It is widely recognized as a key driver in a country's economic and social growth and sustainable development, for example, improvement of employment levels, particularly among women and lower-income countries, reduction in income inequality, enhance consumer spending, promote greater investment in human capital, and directly assist low-income individuals in

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managing risks and coping with financial shocks [2], [3]. Digital finance also enables contactless transactions and supports the quick deployment of government aid, while driving economic growth and reducing financial inequalities. Besides, digital financial inclusion (DFI) also can reduce poverty by enhancing access to financial services and increasing economic opportunities for marginalized populations, thus contributing to long-term sustainable development goals (SDGs).

Despite the promise of DFI, several challenges imposed, for example, lack of access, risks in using DFS, and lack of financial and digital literacy. Access to DFS remains a significant challenge, especially in areas with poor infrastructure. In developing regions, unreliable internet connections often make it difficult for people to perform simple tasks like checking their account balances or transferring money, which can discourage them from using digital platforms [4]. Furthermore, technical problems like system outages or complicated sign-up processes can frustrate users. For those who are unfamiliar with technology, they feel complicated by one-time passwords and authentication steps. Hence, to enhance the accessibility of DFS to everyone, simpler process and better infrastructure are strongly encouraged.

Globally, approximately 230 million adults employed in the private sector and receive their wages in cash are the one who lack access to transaction accounts [5]. Among these individuals, around 78 percent own a mobile phone. This indicates that while these individuals have the ability to access DFS via their mobile phones, they choose not to do so. Therefore, the target variables, ability to be digitally financially inclusive and access to DFS, differ in definition. According to Demirguc-Kunt et al. (2018), Global Findex 2017 found that about 20% of individuals who had an account did not use it at all. Although some individuals have an account with a financial institution and have access to various DFS, they choose not to utilize these services. Hence, the target variables, access to DFS and usage of DFS, are distinct.

Recent studies employ ML algorithms analyse huge datasets by discovering the hidden patterns in socio-demographic factors to identify barriers to DFI [6], [7]. For instance, supervised ML algorithms such as random forests and decision tree are able to which category of people is likely to be financially excluded. Other feature importance tools in ML also offer transparency, making it easier to interpret results into policy action [8]. The outcomes from ML prediction allow for targeted and data-driven interventions across diverse contexts and countries [9]. Hence this study highlight that ML models can support financial inclusion, consistent with the past literature [10].

Hence, the objective of this study is to employ ML algorithms to examine the socio-demographic factor that most strongly predicts the likelihood of using DFS in Nigeria.

The novelty of this study is the use of ML algorithms in identifying the barriers to DFI in Nigeria across the dataset in the years 2017 and 2021. The J48 decision tree algorithm by using WEKA software shows that the accuracy rates for the prediction of DFS target variables have improved from the year 2017 to 2021. Furthermore, the J48 decision tree diagrams from this study offer valuable insights in identifying the most critical socio-economic factor that predict the adoption of DFS. This study contributes to the academic literature by using ML algorithms to identify the barriers to DFI and add value to the world today with a full or rich dataset that can provide meaningful interpretations from the results. This study can serve as a basis for future studies related to digital adoption and financial inclusion in other regions or countries.

2. LITERATURE REVIEW

DFI refers to the use of digital technologies to provide underserved and excluded populations with access to formal financial services [11]. It leverages tools such as mobile phones, internet connectivity, and fintech platforms to deliver banking, payments, credit, and savings services to individuals who lack access to traditional financial institutions. DFI has gained global attention as a critical means to expand financial access, particularly in regions where physical banking infrastructure is limited. Another study also proved that even the traditional financial inclusion was declining, the DFI still increased between 2014 and 2017 [12].

2.1 Key Measures in DFI

2.1.1 Ability

The ability to participate in digital finance depends significantly on owning basic digital tools like mobile phones and having internet access. These factors are crucial for enabling individuals to connect with and use DFS. However, economic constraints can create significant barriers. As found [13] some individuals are too poor to use the formal financial services. Hence, they might not be able to own a mobile phone or access to internet, and this issue excludes them from digital finance opportunities. Addressing these barriers is essential to foster inclusivity and ensure that DFS are accessible to everyone, regardless of their financial background. Thus, the target variable "ability" is included in this study with the indicators, mobile phone ownership or internet access.

2.1.2 Access

Access is the availability of financial services of adequate quality at costs that are fair and [14]. Past studies utilizing the Global Findex to study on DFI have included access as one of the important key measures, but the indicators used were different. For example, the indicators of [15] for the "Micro Access Index" are mobile phone ownership or internet access, the indicators of [16] for "access" are the use of mobile phone or internet to access financial account or check bank balance, while the indicators of [19] for "accessibility" are ownership of debit card, credit card, or mobile money account. The indicators of access used in this study will be the ownership of an account in financial institutions or mobile money account, as the ownership of mobile phones or internet access do not necessarily mean that the individuals are available for the wide range of DFS.

2.1.3 Usage

Usage of DFS involves the active use of these services [15]. The past studies including [15-20] and [21] used the actual use of DFS as the indicator, such as received wage payments into an account or to a mobile phone or to a card, made bill payments online using the internet or using an account, and others. Thus, the usage in this study employed the indicators of actual usage of DFS.

Overall, the studies by [18], using measures such as ownership and usage of financial products, and employing the Micro Access Index, Micro Usage Index, and Micro Digital Financial Inclusion Indices [15], along with [19], focusing on accessibility and usage, all demonstrate that factors like gender, age, educational attainment, income level, employment status, and urbanicity significantly influence DFI. Additionally, [17] found that access and usage are also impacted by these socio-demographic factors, as well as by mobile phone ownership and internet access.

2.2 Methodologies in Exploring the Relationship between Socio-economics Factors and Financial Inclusion

Several traditional methodologies have been utilized in the literature to examine the relationship between socio-demographic factors and DFI across various regions. By using a two-step principal component analysis (PCA) method, [15] are able to create a DFI index in MENA. Their study also used Heckman selection methodology to identify the primary drivers of DFI in MENA countries. The measures of DFI in this study include the index, access, and usage. The index formed based on the ownership of an account, access based on the ownership of mobile phone or internet access, while usage based on the use of DFS. In addition, [16] used a bivariate probit model to find the features that stimulate the users to make digital payments in the three regions in the developing countries, namely East Asia Pacific, South Asia and Sub-Saharan Africa. Furthermore, [17] leveraged the Global Findex data in the year 2014, 2017, and 2021 to evaluate the factors influencing the access and usage of DFS in 39 African countries. The authors scrutinized PCA and instrumental variable probit methodology to investigate the key drivers that promote DFI in Africa. Moreover, [18] applied logistic regression model to explore the relationship between socio-economic factors and the accessibility and usage of DFS in India. The measures of DFI in their study include accessibility and usage. The accessibility was examined based on indicators like ownership of credit or debit card, or mobile money account, while the usage was based on any use of DFS. Next, [21] made use of regression model to examine the socio-economic characteristics, mobile phone ownership and banking behaviour as key determinants of DFI in India. These studies highlight a variety of methods used to explore DFI; each tailored to specific questions and regions. For instance, PCA is a popular tool for building composite indices that provide a broad view of financial inclusion levels. Models like bivariate probit and logistic regression are useful for examining how socio-demographic factors influence specific outcomes, such as whether people access or use DFS. Meanwhile, instrumental variable methods help tackle challenges like endogeneity, making it easier to identify causal links. However, these methods have their limitations. Traditional analytical methods often struggle to pinpoint which factor is the most important or to capture the interactive effects between factors.

2.3 Research Gaps

Despite the extensive body of literature examining the factors influencing financial inclusion, there is currently a methodological gap in research when it comes to applying ML models to study DFI. Most of the existing studies have utilized traditional statistical tools and econometric methods, such as regression analysis or hypothesis testing, to analyse the impact of various socio-economic factors on financial inclusion. These methods, while effective in identifying relationships between variables, are often limited by their inability to identify the most influencing factor or provide insights into interaction effects between variables. ML, particularly decision tree algorithms such as J48, addresses these challenges more effectively. ML models can automatically learn complex patterns from the data, handle large datasets efficiently, and capture nonlinear relationships without needing to specify interaction terms explicitly. These models can also deal with noisy or missing data more robustly, providing better generalization to unseen data. Moreover, they allow for the evaluation of feature importance, offering insights into which factors contribute most to DFI.

By applying ML models to this field, this study aims to fill the gap in existing research and provide more comprehensive analyses of the factors that influence DFI. This approach offers significant advantages over conventional methods and can contribute to more informed policy decisions aimed at improving access to financial services. Next, existing studies on DFI have primarily focused on two key measures, access and usage. For example,[15] defined access based on the use of mobile phone or internet to access financial institution account, while usage is measured by the utilization of DFS. Similarly, [19] assessed access in terms of debit or credit card or mobile money account ownership and usage as any activity involving DFS. While these studies separate the concepts of access and usage, they do not explicitly distinguish "ability", a foundational measure that evaluates whether individuals have the necessary infrastructure, such as mobile phones or internet access, to achieve inclusion, and further the "access", that enable individuals available to a wide range of DFS. This study fills this gap by introducing "ability" as a separate and essential measure alongside access and usage. By focusing on these prerequisites, it highlights that having the ability to connect to digital platforms is a vital first step before access and usage can even be considered, offering a clearer framework.

3. RESEARCH METHODOLOGY

This study utilized individual-level data from the Global Findex 2017 and 2021 database. Global Findex database is an extensive and globally recognized resource developed by the World Bank. The Global Findex collects questionnaires based on nationally representative surveys of over 150,000 adults aged 15 and above. It offers comprehensive indicators of the use of financial services across 175 countries. To warrant a representative sample that mirrors the diversity within each country, these surveys implemented a multi-stage stratified random sampling methodology, stratified by location (urban or rural) and region.

In this study, the individual-level data of Nigeria from both 2017 and 2021 were utilized. In the data cleaning stage, the rows of data consisting of blank, "do not know", or "refused to answer" responses, were removed to establish the integrity of the data analysis. This process was applied to all datasets over two years. Table 1 summarizes the target variables used and their attributes in this study. The target variable is DFI as proxied by ability, access or usage.

Gender inequality often appears in access to financial services or technology as women encounter social or cultural barriers. Age is relevant as older populations may struggle with the use of digital devices due to a lack of trust and familiarity, whereas youth tend to be more tech-savvy and open to using digital platforms. Education is important for understanding and utilizing DFS. Educated people are more likely to navigate online banking tools and trust digital systems effectively. The income level will affect the use of DFS as low-income people may lack the financial resources to access the tools required for DFI. On the other hand, higher-income people are more likely to own smartphones, subscribe to internet access, and manage bank accounts. Employment will affect DFS as unemployed people rely more on cash, whereas employed people receive wages via bank transfers. Lastly, urbanicity does influence DFS as urban areas provide better infrastructure such as financial institutions, internet connectivity and mobile networks. People in rural areas often face challenges such as poor network coverage, lack of nearby banks, and limited digital literacy.

Table 1. Target Variables and Their Attributes

Target Variables	Criteria
Ability to be digitally financial inclusive	"Yes" if either of the mobile phone ownership or internet access satisfied
Access to DFS	"No" if both of the mobile phone ownership or internet access not satisfied
Usage of DFS	"HasAcc", if the respondent has an account at a financial institution, a mobile money account, or both
Attributes	Criteria
Gender	Categorized as "female" and "male".
Age	Respondent aged between 15 and 39 known as "youth". Respondent aged between 40 and 59 known as "middle age". Respondent aged above 59 known as "old".
Education	Categorized into "primary or less", "secondary", and "tertiary or above".
Income Quintile	Categorized into "poorest 20", "middle 60", and "richest 20".
Employment	Categorized as "out of workforce" and "in workforce".

Figure 1 is the conceptual framework of this study. It describes the relationship between socio-demographic factors (attributes) and various aspects of DFI (target variables). The attributes include gender, age, education level, income quintile, employment status, and urbanicity, which are expected to influence three key aspects of DFI: ability (access to mobile phones and the internet), access (having an account at a financial institution or mobile money provider), and usage (the use of DFS).

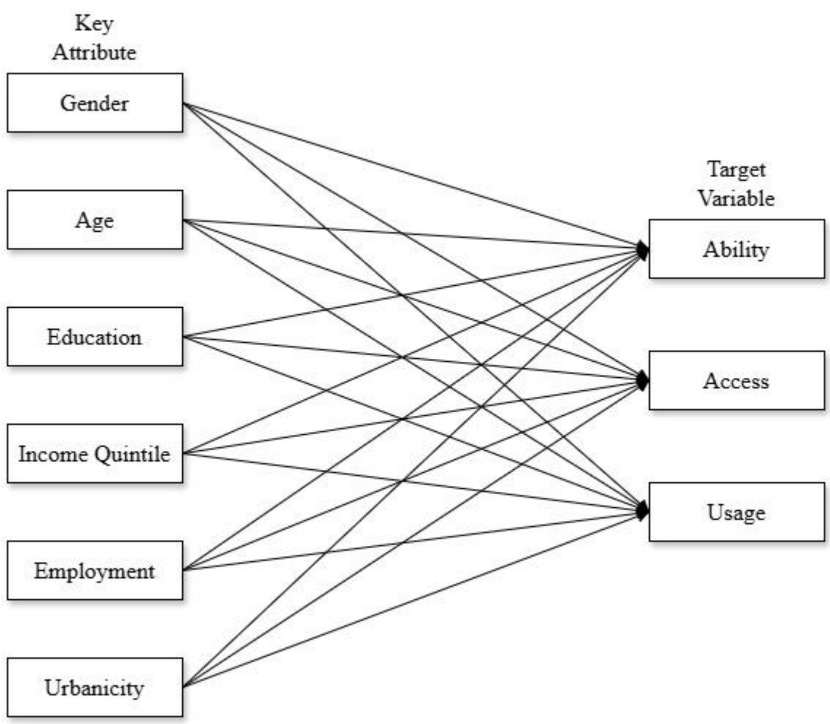

Figure 1. Conceptual Framework

To analyse these relationships, the J48 decision tree algorithm is employed using the WEKA software. J48 is a supervised learning classifier that builds decision trees by recursively splitting the dataset based on attribute values that yield the highest information gain, making it well-suited for this study that use categorical data. The algorithm operates by selecting the attributes (gender, age, educational attainment, income level, employment status, and urbanicity) that best separate the data into distinct classes at each node, constructing a tree structure that can be easily interpreted and visualized. Pruning techniques are applied to reduce overfitting by removing branches that do not contribute significantly to classification accuracy. J48 was chosen due to its interpretability, which is critical for policy implications in financial inclusion studies. It allows policymakers to trace back and understand the decision-making logic to improve the DFI. Additionally, J48 performs well with relatively small datasets in this study that consists of 977 datasets in year 2017 and 987 data in year 2021. The J48 algorithm helped identify which socio-demographic factors have the strongest effect on DFI and how these factors interacted with each other. Default settings were used for the model configuration, with a confidence factor of 0.25 for pruning and a minimum number of instances per leaf set to 2. A 10-fold cross-validation method was employed to validate the model. By using this approach, the study aims to discover insights into the drivers of DFI in Nigeria.

4. RESULTS AND DISCUSSIONS

4.1 Descriptive Summary

As shown in Table 2, the average age of respondents is 31.62 years. Gender distribution shows that males make up 58.4% of the respondents, while females account for 41.6%. Regarding education, the majority (75.4%) have attained secondary education, while 21.8% have primary education or less, and only 2.8% have tertiary education. Income distribution shows that 14.6% of respondents fall within the poorest 20%, 55.7% in the middle 60%, and 29.7% in the richest 20%. Employment data indicates that 78.1% of respondents are in the workforce, while 21.9% are out of the workforce. The ability to be digitally financially included is high, with a mean of 0.776, suggesting that 77.6% of the population has access to mobile phones or the internet. Access to DFS has a mean of 0.566, indicating around half of the population has the access. However, the usage of DFS, with a mean of 0.348, remains relatively low.

Table 2. Descriptive Statistics of the Year 2017 and 2021 Dataset

	2017		2021	
Attributes	Mean	Standard Deviation	Mean	Standard Deviation
Ability	0.776	0.417	0.845	0.362
Access	0.566	0.496	0.621	0.485
Usage	0.348	0.476	0.519	0.500
Age	31.615	13.871	31.503	11.834
Gender				
Female	0.416	0.493	0.436	0.496
Male	0.584	0.493	0.564	0.496
Education Level				
Primary or less	0.218	0.413	0.212	0.409
Secondary	0.754	0.430	0.748	0.434
Tertiary or more	0.028	0.164	0.041	0.197
Income Quintile				
Poorest 20	0.146	0.353	0.159	0.366
Middle 60	0.557	0.497	0.530	0.499
Richest 20	0.297	0.457	0.311	0.463
Employment				
In workforce	0.781	0.414	0.793	0.405
Out of workforce	0.219	0.414	0.207	0.405

The mean age is 31.5 years, and the gender distribution is distributed as 43.6% females and 56.4% males. Education levels show a majority has completed secondary education, with 74.8% of individuals having completed at least secondary schooling, and following 21.2% completed primary or less, and 4.1% completed tertiary or more. Income distribution shows 53% in the middle 60% income quintile, 15.9% in the poorest 20, and 31.1% in the richest 20%. Employment data suggests that 79.3% of individuals are in the workforce, while 20.7% out of workforce. Urban residents, making up 65.9% of the population, while the remaining 34.1% live in rural areas. Table 4 shows that a significant portion of the population, which is 84.5%, has the ability to be digitally financially included. However, access to DFS stands at 62.1%, indicating that while many people have the ability, there are still barriers limiting access for a portion of the population. The usage of DFS is also notable at 51.9%, highlighting that more than half of the respondents are actively using these services.

4.2 Classifier Output from ML Decision Tree Algorithm

Table 3 depicts the performance evaluation results for the data year 2017 based on J48 decision tree across three dimensions of DFI: ability, access, and usage. The accuracy rate for the ability of DFS is 77.6% with the root mean squared error (RMSE) of 0.417. On the other hand, the accuracy rate for the access of DFS is 72.4% with the RMSE of 0.4422. Lastly, the accuracy rate for the access of DFS is 69.1% with the RMSE of 0.4497. The highest classification accuracy detected for DFS ability which indicates that the model is most effective at predicting whether individuals possess the ability to engage with DFS (e.g., having access to mobile phones and the internet). The relatively lower root mean square error further recommends that the model makes fewer prediction errors in this category. As the accuracy of all models exceeds the baseline random chance level of 50, the models demonstrate satisfactory classification performance. Moreover, the results are consistent with those reported in the existing literature, reinforcing the model's reliability and validity [22].

Table 3. Performance Evaluation Results for the Data Year 2017 Based on J48 Decision Tree

	Ability		Access		Usage	
Correctly Classified Instances	758	77.6%	707	72.4%	675	69.1%
Incorrectly Classified Instances	219	22.4%	270	27.6%	302	30.9%
Kappa Statistic	0		0.417		0.2407	
Mean Absolute Error	0.3478		0.3852		0.3994	
RMSE	0.417		0.4422		0.4497	
Relative Absolute Error	99.90%		78.41%		88.00%	
Root Relative Squared Error	99.99%		89.22%		94.41%	
Total Number of Instances	977		977		977	

Table 4 demonstrates the performance evaluation results for the data year 2021 based on J48 decision tree across three dimensions of DFS: ability, access, and usage. The accuracy rate for the ability of DFS is 85.6% with the RMSE of 0.3393. On the other hand, the accuracy rate for the access of DFS is 73.3% with the RMSE of 0.4367. Lastly, the accuracy rate for the access of DFS is 67.3% with the RMSE of 0.4564. the performance for usage slightly declined compared to the year 2017, suggesting that persistent barriers in converting access into actual DFS usage, such as trust and digital literacy. The highest classification accuracy was detected for DFS ability again, similar to the data for the year 2017, which indicates that the model is most effective at predicting whether individuals possess the ability to engage with DFS. This improvement indicates improved model precision and a decrease in prediction errors, possibly due to greater adoption of digital infrastructure or improved data quality over time.

Figures 2 to 4 show the diagrams of J48 decision tree on the factors that predict DFI with the target variable of ability, access and usage, respectively. Table 5 summarizes the root node and first split level for the target variables of DFI which is proxied by ability, access and usage based on the data in the years 2017 and 2021. In 2017, the root nodes and first-level splits for both the "Access" and "Usage" were education and gender respectively. This indicates that educational attainment and gender differences significantly influenced access and usage of DFS in Nigeria. In 2021, "Ability" was shifted to be influenced by education as the root node, followed by gender as the first-level split. For "Access", education remained the root node, while employment and age became the first-level split, with individuals who completed secondary education split by employment and those who have primary education or less split by age. Education continued to be the root node for "Usage", while gender for individuals with primary education, and income for individuals with secondary education, emerged as the first-level splits.

Table 4. Performance Evaluation Results for Data Year 2021 Based on J48 Decision Tree

	Ability		Access		Usage	
Correctly Classified Instances	845	85.6%	723	73.3%	664	67.3%
Incorrectly Classified Instances	142	14.4%	264	26.7%	323	32.7%
Kappa Statistic	0.2872		0.3877		0.3422	
Mean Absolute Error	0.2226		0.3735		0.3949	
RMSE	0.3393		0.4367		0.4564	
Relative Absolute Error	84.80%		79.34%		79.08%	
Root Relative Squared Error	93.76%		90.02%		91.34%	
Total Number of Instances	987		987		987	

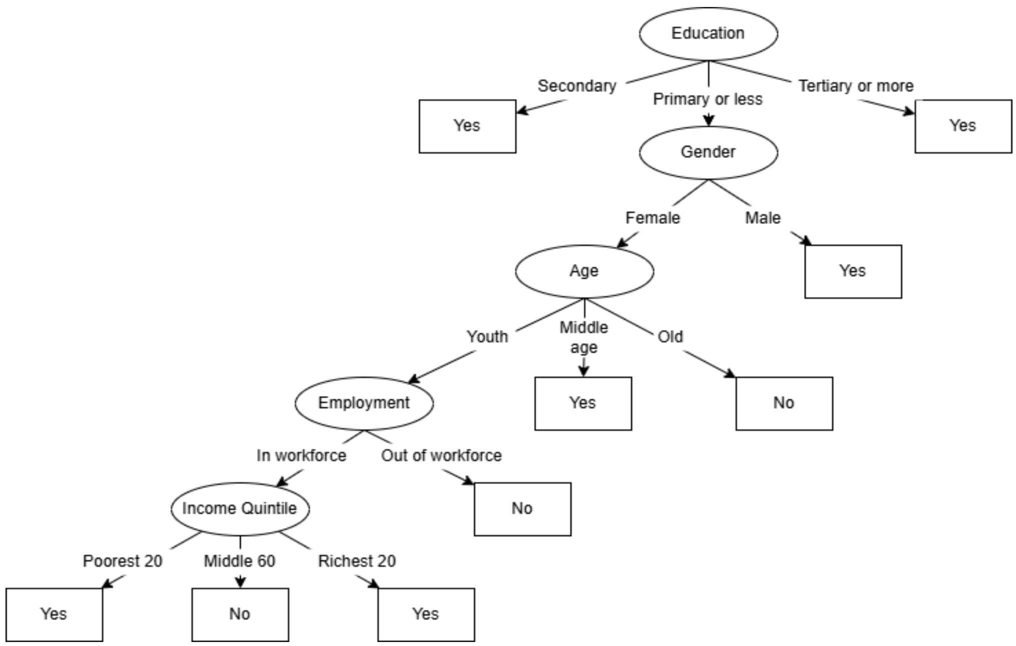

Figure 2. Decision Tree Diagram on the Prediction of DFS (Ability) with Socioeconomic Factors (Year 2021)

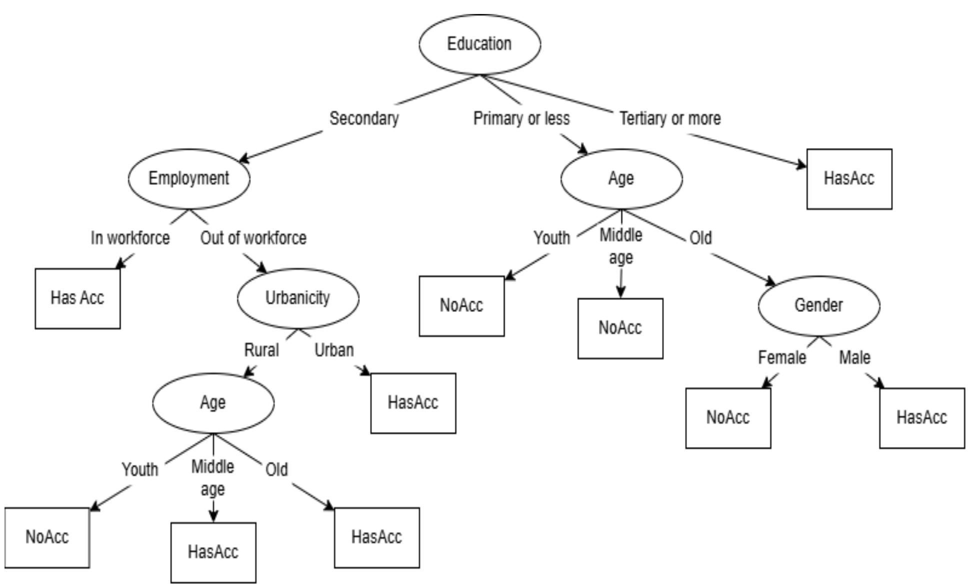

Figure 3. Decision Tree Diagram on the Prediction of DFS (Access) with Socioeconomic Factors (Year 2021)

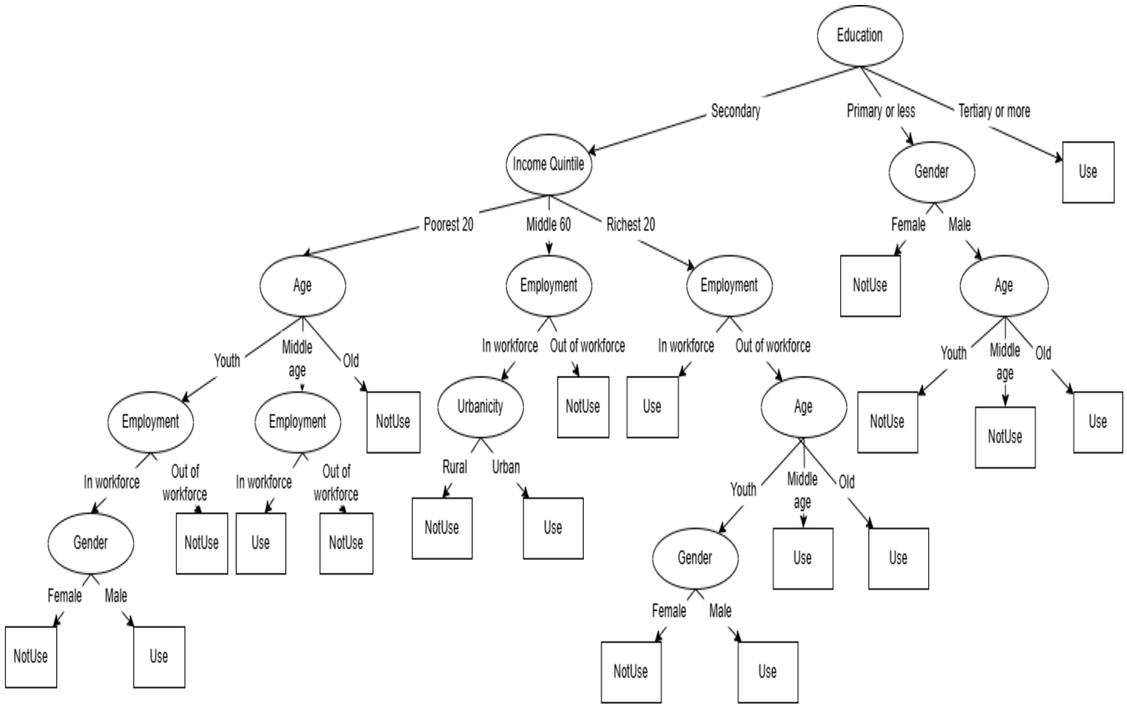

Figure 4. Decision Tree Diagram on the Prediction of DFS (Usage) with Socioeconomic Factors (Year 2021)

Table 5. Summary of the Root Node and first-level split on the prediction of DFS (Ability, Access, Usage) in the year 2017 and 2021

		Ability	Access	Usage
2017	Root Node	Education	Education	Education
	First-level split	Gender	Age (Primary)	Gender (Primary)
2021	Root Node	Education	Education	Education
	First-level split	Gender	Age (Primary)	Gender (Primary)

The findings for Nigeria indicate a persistent influence of education and gender on DFI from 2017 to 2021. While education consistently shaped "Access" and "Usage", the introduction of employment, income, and age as key factors in 2021 suggests that economic participation and demographic characteristics play increasingly prominent roles. Addressing gender disparities and expanding educational and employment opportunities will be critical for enhancing DFS adoption in Nigeria.

Overall, the results disclose that the model steadily performs best in forecasting the ability feature of DFS and proves satisfactory classification performance across all three dimensions. The enhancements observed in 2021 highlight rising digital willingness among the Nigerian population, though challenges remain, predominantly in nurturing actual usage of DFS.

5. CONCLUSION

Nigeria verified persistent barriers, with education and gender significantly shaping "Access" and "Usage" across both years, in conjunction with increasing roles for employment, income, and age in 2021. Addressing these gaps will involve actions to solve gender inequalities and improve prospects for education and employment. These factors combined highlight the complexity of DFI and the need for tailored interventions that address both enabling factors and barriers across different socio-demographic groups in Nigeria.

This study highlights barriers to DFI, providing governments with a comprehensive understanding of the socio-demographic landscape and the most influencing factor. Determinants such as high education levels, higher income quintiles, and urban residence indicate which groups are more likely to adopt DFS, guiding policymakers to expand programs that leverage these strengths. Simultaneously, barriers like low education, low income, rural residence, and gender disparities need targeted interventions. By addressing these barriers through initiatives like digital literacy campaigns, rural internet expansion, and gender-inclusive financial policies, governments can create an equitable digital financial ecosystem that maximizes participation across all socio-demographic groups. By focusing on the most important factors influencing DFI, governments also can maximize the impact of their efforts.

For digital financial service providers and other relevant stakeholders, the findings emphasize the importance of creating tailored solutions that address both the opportunities and challenges of DFI. Determinants like higher education, higher income, and urban residency reveal groups that are more likely to adopt DFS, allowing service providers to focus on enhancing and innovating services for these segments. On the other hand, barriers such as low education, low income, rural living, and gender inequality highlight underserved groups requiring specialized attention. By designing targeted initiatives such as simplified user interfaces, affordable service options, and outreach programs for rural and female users, service providers can expand their reach and drive greater adoption. Addressing these key factors effectively ensures that DFS solutions meet the needs of diverse socio-demographic groups, fostering financial inclusion on a broader scale. For ability, Nigeria needs to address gender and educational disparities. For access, Nigeria should focus on reducing unemployment and income disparities. For usage, meanwhile, Nigeria should focus on strategies to bridge educational and gender gaps.

It is important to emphasize the role of ML, particularly the J48 decision tree algorithm, in identifying the socio-demographic factors affecting DFI in Nigeria. It effectively handles both categorical and continuous data, allowing for a clearer understanding of factors such as education, income, and gender. The model's ability to split data into subsets enables a deeper insight into which factors most influence access and usage of DFS. In conclusion, the J48 decision tree model is a valuable tool in uncovering patterns in DFI.

The limitation of this study is the hyperparameters of the ML model were set at their default settings, limiting the model's precision. The hyperparameter tuning should be implemented to enhance and obtain a higher model precision.

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AUTHOR CONTRIBUTIONS

Yin Ting Chin: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
Hui Shan Lee: Project Administration, Supervision, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

This study uses secondary data provided by the Global Findex database. No human or animal is involved. Our publication ethics follow The Committee of Publication Ethics (COPE) guideline, https://publicationethics.org/.

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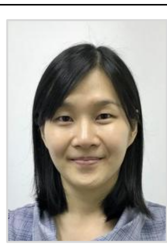	**Hui Shan Lee** is an associate professor in Universiti Tunku Abdul Rahman. Her research areas are financial economics, environmental economics, corporate governance and insurance. She can be contacted at email: hslee@utar.edu.my.